

## Article

# SSRES: A Student Academic Paper Social Recommendation Model Based on a Heterogeneous Graph Approach

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**Abstract:** In an era overwhelmed by academic big data, students grapple with identifying academic papers that resonate with their learning objectives and research interests, due to the sheer volume and complexity of available information. This study addresses the challenge by proposing a novel academic paper recommendation system designed to enhance personalized learning through the nuanced understanding of academic social networks. Utilizing the theory of social homogeneity, the research first constructs a sophisticated academic social network, capturing high-order social relationships, such as co-authorship and advisor–advisee connections, through hypergraph modeling and advanced network representation learning techniques. The methodology encompasses the development and integration of a hypergraph convolutional neural network and a contrastive learning framework to accurately model and recommend academic papers, focusing on aligning with students’ unique preferences and reducing reliance on sparse interaction data. The findings, validated across multiple real-world datasets, demonstrate a significant improvement in recommendation accuracy, particularly in addressing the cold-start problem and effectively mapping advisor–advisee relationships. The study concludes that leveraging complex academic social networks can substantially enhance the personalization and precision of academic paper recommendations, offering a promising avenue for addressing the challenges of academic information overload and fostering more effective personalized learning environments.

**Keywords:** information recommendation; social recommendation; heterogeneous information networks; social network analysis; contrastive learning

**MSC:** 68-04

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## 1. Introduction

In an era defined by rapid advancements in information science and technology, the academic world has undergone a significant transformation, marked by an exponential growth in electronic literature. This surge in scholarly publications has heralded the onset of the “academic big data age”, bringing forth challenges such as information overload and learning disorientation. These challenges have made it increasingly difficult for students and researchers to navigate the vast sea of academic data and to find literature relevant to their research interests [1–7]. In response, academic paper recommendation systems have emerged as crucial tools. By leveraging sophisticated algorithms, these systems offer personalized recommendations that closely align with individuals’ research interests and directions, thus significantly enhancing the efficiency of academic research.

However, the utility of these systems is challenged by the vast scope of academic data and the complexity of pinpointing users’ interests. The essential task is to refine these systems for better navigation through the academic social fabric, thus elevating recommendation accuracy. There is a pressing need for advanced systems that can adeptly handle academic nuances and social network dynamics, bridging the resource–needs gap within the scholarly community more effectively.

The academic paper recommendation systems employ diverse strategies like content-based filtering, collaborative filtering, graph-based approaches, and hybrid models to link researchers with pertinent literature [8–15]. However, issues like data sparsity and the cold-start problem persist, hindering their efficacy by veiling users' specific preferences, especially for new or seldom-interacted items. Our research proposes integrating social relationships into the recommendation framework, drawing on social science insights regarding the impact of social networks on individual preferences and decisions. This novel approach aims to improve recommendation accuracy and personalization by leveraging academic social networks, addressing key challenges and marking a methodological advancement in the field.

In the rapidly advancing fields of academic research and artificial intelligence, exploring complex academic networks, spanning co-authorships, citations and advisor–advisee relationships, presents both significant potential and challenges. These networks are vital for understanding scholars' academic paths but are difficult to analyze due to their dynamic and intricate nature. Current academic paper recommendation systems often simplify these relationships, neglecting the nuanced dynamics of higher-order social interactions and the full spectrum of academic collaborations. This leads to an incomplete modeling of academic social networks, thereby hindering system performance. Additionally, despite the success of graph-based models, the utilization of hypergraph structures for capturing complex social relationships remains underexplored. Coupled with the challenges of acquiring high-quality labeled data and the scarcity of interaction data, the effectiveness of these models is limited. Moreover, the role of academic papers as central nodes rich in semantic information and intricate interactions is often overlooked in representation learning. Addressing these gaps and recognizing the multifaceted interactions within academic networks could significantly enhance recommendation accuracy and personalization.

Addressing these gaps, our study proposes a comprehensive approach that minimizes the dependency on student–paper interaction data and thoroughly captures the constructed complex multiple academic social relationships and the intricate interactions within heterogeneous academic literature networks. By learning the node representations of students and academic papers comprehensively, this work aims to optimally provide students with the academic paper resources that best meet their learning needs, marking a significant advancement in the field of academic paper recommendation systems.

In this study, we introduce the Student Academic Paper Social Recommendation Model (SSRES), a novel framework developed to mitigate the sparse interaction dilemma between students and academic papers in recommendation systems. Initially, SSRES meticulously constructs a complex academic social network by modeling high-order social relationships, such as co-authorship and co-citation, which forms the basis for a more relevant recommendation output. Progressing further, the model enriches the multi-relational network through the extraction of advisor–advisee relationship dynamics and academic team collaboration insights. Employing a contrastive learning approach, SSRES effectively captures and represents the nuanced interaction patterns between students and academic papers, decreasing the traditional reliance on extensive interaction data. The framework integrates self-supervised learning techniques inspired by social theories and a heterogeneous graph approach, fine-tuning user embeddings to enhance the personalization of the recommendation process. Each step in the development of SSRES represents a strategic move towards a comprehensive solution for personalized academic paper recommendations that cater specifically to the individualized learning requirements of students.

The major contributions of this work are summarized as follows:

- The development and implementation of SSRES, a novel framework that integrates high-order social relationships into the fabric of academic social networks through the adept utilization of hypergraphs. This framework combines transition mechanisms with advanced network representation learning to encode nuanced co-authorial interactions, enabling the automated and precise delineation of advisor–advisee relationship dynamics and academic collaboration networks.

- The introduction of a dual-structured enhancement to the recommendation process, including a ‘cross-social relation contrastive’ learning framework for refining student representations and a parallel contrastive learning strategy for academic papers. This approach enriches the representational depth of the student academic social network and provides a comprehensive framework for academic paper representation.
- A synergistic integration of the core recommendation task with advanced self-supervised learning frameworks, facilitating a holistic optimization approach that uncovers students’ latent preferences. This strategy not only advances the precision of academic paper recommendations but also demonstrates the effectiveness of SSRES through empirical evaluations on real-world datasets.

## 2. Related Work

### 2.1. Advisor–Advisee Relationship Identification

The exploration of advisor–advisee relationships within academic networks has garnered significant attention, reflecting the importance of accurately mapping the intricate web of scholarly interactions. Among the various relationships forming the foundation of academic networks, the advisor–advisee relationship stands out as pivotal, influencing the formation of collaborative teams and the modeling of academic entities [16–22]. This pursuit falls under the category of relationship mining, a critical aspect of social network analysis, with the potential to benefit academic applications, such as double-blind peer reviews and the generation of academic genealogies. In addressing the challenges associated with extracting advisor–advisee relationships from dynamic and complex academic collaboration networks, several researchers have proposed innovative solutions. Notably, Wang et al. [23] introduced the TPFG model, designed to extract advisor–advisee relationships by leveraging the network’s inherent structure and the rich semantic information of nodes and edges. Zhao et al. [24] proposed the deep learning-based tARMM model, which recognizes advisor–advisee relationships through a sophisticated analysis of academic collaboration networks. Further advancing the field, Wang et al. [25] developed the Shifu model, a deep learning approach that not only identifies advisor–advisee relationships but also contributes a large-scale mentorship relationship dataset for future research endeavors. These models underscore the field’s movement towards more nuanced and effective methods of identifying advisor–advisee relationships, acknowledging the limitations posed by the lack of high-quality, real-world advisor–advisee relationship data.

Despite these advances, the current methodologies for advisor–advisee relationship identification face limitations, particularly in fully utilizing the network structure information and the semantic richness of the academic collaboration networks. The challenge lies in automating the extraction of advisor–advisee relationships from academic collaboration networks, a task made difficult by the networks’ dynamic nature and the scarcity of quality advisor–advisee relationship data. This gap highlights a critical area for future research, aiming to enhance our understanding of academic communities from the perspectives of team formation and academic entity modeling.

### 2.2. Social Recommendation

In the realm of information filtering technology, recommendation systems have become integral to enhancing user experience across various platforms, from Amazon’s product suggestions to Douban’s book recommendations. However, traditional algorithms face challenges like sparsity and the cold-start problem. Inspired by social science theories that suggest a user’s preferences and decisions are often influenced by their social circle, researchers have integrated social network data into recommendation systems for more personalized suggestions [26,27].

Early explorations primarily focused on matrix factorization techniques. For instance, “Sorec” proposed by Ma et al. [28] was among the first to incorporate social network information to address data sparsity. Ma et al. [29] further developed this concept through “social regularization”, enhancing the model’s ability to leverage social connections for

improved recommendations. Yang et al. [30] introduced a trust-based social collaborative filtering approach, emphasizing the significance of trust in refining recommendation quality. Yin et al. [31] and Yin et al. [32] explored group dynamics, showcasing how understanding social influence within groups could lead to more accurate group recommendations.

With the advent of deep learning, graph neural networks (GNNs) have broadened the scope of social recommendations. Zhou et al. [33] provided a comprehensive review of GNN methods and applications, laying the groundwork for their use in capturing complex user interactions. “GraphRec”, introduced by Fan et al. [34], marked the first application of GNNs to social recommendation, demonstrating the networks’ capability to model the intricate web of user and item interactions effectively. Subsequent studies by Wu et al. [35], Song et al. [36] and Wei et al. [37] further expanded on this foundation, introducing models like “Dual Graph Attention Networks” and “Dynamic Graph Attention Networks” to represent multifaceted social effects in recommender systems.

Extensive research has focused on integrating social data and developing new algorithms to improve the performance of recommendation systems. However, in the field of academic recommendation systems, the comprehensive integration of complex academic social relationships to provide personalized and precise recommendations remains relatively neglected. The existing literature primarily concentrates on utilizing basic social relationships or trust information to enhance recommendations. Nonetheless, there is a noticeable gap in research on effectively capturing and leveraging the multi-dimensional features of student social relationships, as well as improving recommendation accuracy in cold-start scenarios.

### 2.3. Contrastive Learning in Self-Supervised Learning

In recent years, self-supervised learning has achieved remarkable success across various domains, including image processing and natural language processing. Among the techniques under the umbrella of self-supervised learning, contrastive learning has particularly drawn widespread attention from researchers due to its effective learning paradigm [38,39]. This approach learns low-dimensional, dense embeddings by contrasting positive and negative samples within the data, enabling the model to learn distinctive embeddings even in the absence of labels. The application of contrastive learning has been extended to the field of graph representation learning, showing considerable potential when integrated with recommendation systems, although research in this area remains relatively nascent.

Velickovic et al. [40] introduced the Deep Graph Infomax (DGI) model, which constructs local and global representations in the form of sample pairs and utilizes the Infomax principle for contrastive learning. Peng et al. [41] proposed the Graph Mutual Information (GMI) model, which contrasts the central node and its local representations from both node features and topological structures perspectives. Hassani et al. [42] developed the Multi-View Graph Representation Learning (MVGR) model, focusing on contrasting multiple different views. Lastly, Park et al. [43] presented the Deep Multi-Graph Infomax (DMGI) model, which contrasts local and global representations of graphs on attributed multiplex networks and designs a consensus regularization framework to integrate embeddings from multiple graphs.

However, these existing models primarily focus on general graph representation tasks and do not specifically address the unique challenges posed by recommendation systems. For academic recommendation systems, there is a lot of information on advisor–advisee relationships and social science theories that needs to be specially addressed to improve model performance. For self-supervised learning, work that takes into account multiple aspects of information is still relatively rare and warrants further exploration.

## 3. Preliminaries

This section introduces the foundational concepts and definitions upon which our study builds. The task of this paper is to provide personalized academic paper recommendations to students. In the recommendation process, let  $\mathbf{A} = \{a_1, a_2, a_3, \dots, a_m\}$  and

$\mathbf{P} = \{p_1, p_2, p_3, \dots, p_n\}$  represent the set of scholars and the set of papers in the recommendation system, respectively, where  $m$  and  $n$  denote the number of scholars and papers, i.e.,  $|\mathbf{A}| = m$  and  $|\mathbf{P}| = n$ . A subset of the scholar set,  $\mathbf{A}_t = \{a_{t1}, a_{t2}, a_{t3}, \dots, a_{t0}\}$ , represents the set of students. The binary rating matrix  $\mathbf{R} \in \mathbb{R}^{m \times n}$  stores the interaction data between scholars and papers, where  $r_{ap} = 1$  indicates an interaction between the scholar and the paper, and  $r_{ap} = 0$  indicates no interaction. Moreover,  $\mathbf{Q} \in \mathbb{R}^{m \times d}$  and  $\mathbf{S} \in \mathbb{R}^{n \times d}$  represent the comprehensive embeddings of scholars and papers, respectively.

### 3.1. Definition 2-1 Heterogeneous Academic Literature Network

A heterogeneous academic literature network is a type of heterogeneous information network that contains multiple types of objects and interaction relationships. Let  $\mathbf{G} = \{\mathbf{V}, \mathbf{E}, \mathbf{B}, \mathbf{D}\}$  represent the heterogeneous academic literature network, where  $\mathbf{V}$  and  $\mathbf{E}$  are the sets of nodes and edges, respectively, and  $\mathbf{B}$  and  $\mathbf{D}$  are the sets of node types and edge types, respectively. In this study, the heterogeneous academic literature network  $\mathbf{G}$  mainly includes three types of nodes, identified as scholars, papers, and citations, denoted by  $\mathbf{A}$ ,  $\mathbf{P}$ , and  $\mathbf{C}$ , respectively; and two types of edges identified as writing and citing, denoted by  $\mathbf{D}_1$  and  $\mathbf{D}_2$ , respectively.

### 3.2. Definition 2-2 Metapath

A metapath  $\pi$  is defined on a heterogeneous information network  $\mathbf{G}$  as a path  $\mathbf{B}_1 \xrightarrow{\mathbf{D}_1} \mathbf{B}_2 \xrightarrow{\mathbf{D}_2} \dots \xrightarrow{\mathbf{D}_l} \mathbf{B}_l$ , often abbreviated as  $\mathbf{B}_1 \mathbf{B}_2 \dots \mathbf{B}_l$ , which defines a composite relationship  $\mathbf{D} = \mathbf{D}_1 \circ \mathbf{D}_2 \circ \dots \circ \mathbf{D}_l$  between the node types  $\mathbf{B}_1$  and  $\mathbf{B}_l$ , where  $\circ$  represents the composition operator. Therefore, metapaths can depict high-order structures containing rich and complex semantic information.

### 3.3. Definition 2-3 Hypergraph

A hypergraph is a generalization of a traditional graph where an edge can connect any number of nodes, providing a natural method for modeling complex high-order relationships. Let  $\mathbf{G}_h = (\mathbf{V}_h, \mathbf{E}_h, \mathbf{W}_h)$  represent the hypergraph, where  $\mathbf{V}_h$  and  $\mathbf{E}_h$  are the sets of vertices and hyperedges, respectively, and each hyperedge can connect any number of vertices. The diagonal matrix  $\mathbf{W}_h$  is the weight set of hyperedges, which, in this study, are uniformly assigned a weight of 1. The hypergraph can be represented by an incidence matrix  $\mathbf{H} \in \{0, 1\}^{|\mathbf{V}_h| \times |\mathbf{E}_h|}$ , where for each vertex  $v \in \mathbf{V}_h$  and hyperedge  $e \in \mathbf{E}_h$ ,

$$\mathbf{H}_{ve} = \begin{cases} 1 & \text{if } v \in e, \\ 0 & \text{if } v \notin e. \end{cases}$$

Let  $\mathbf{D}$  and  $\mathbf{L}$  represent the diagonal degree matrices of vertices and hyperedges, respectively, where

$$\mathbf{D}_{vv} = \sum_{e \in \mathbf{E}_h} \mathbf{H}_{ve}, \quad \mathbf{L}_{ee} = \sum_{v \in \mathbf{V}_h} \mathbf{H}_{ve}.$$

### 3.4. Definition 2-4 Advisor–Advisee Relationship

The advisor–advisee relationship represents the direct knowledge inheritance between scholars, playing a significant role in the learning process of students. This study employs the mentorship relationship  $\mathbf{R}_{aa} = \{r_{ij}\}$ ,  $i, j \in \mathbf{A}$  to denote whether a mentorship relationship exists between scholars  $i$  and  $j$ . If  $r_{ij} = 1$ , it indicates a mentorship relationship where scholar  $i$  is the mentor of scholar  $j$ ; otherwise, if  $r_{ij} = 0$ , it indicates no mentorship relationship exists.

## 4. Construction of Students' Multiple Academic Social Relationships Based on Heterogeneous Academic Networks

In the landscape of academic big data, the imperative to navigate through information overload and enhance learning paths has led to the development of sophisticated academic

paper recommendation systems. Central to these systems is the integration of scholarly social relationships, drawing upon the principle of social homophily to surmount the challenge of sparse interactions. This section unveils a methodological framework for constructing a nuanced scholarly social network, emphasizing the extraction of multifaceted student social relationship features. By harnessing high-order social relationships and the distinct academic backgrounds of scholars, the approach aims to elevate the recommendation system's performance. A detailed exposition of this methodology, including the identification of mentorship relationships and the articulation of a comprehensive academic social network, is provided. The structural diagram illustrating this framework is presented in Figure 1, guiding the reader through the proposed enhancements.

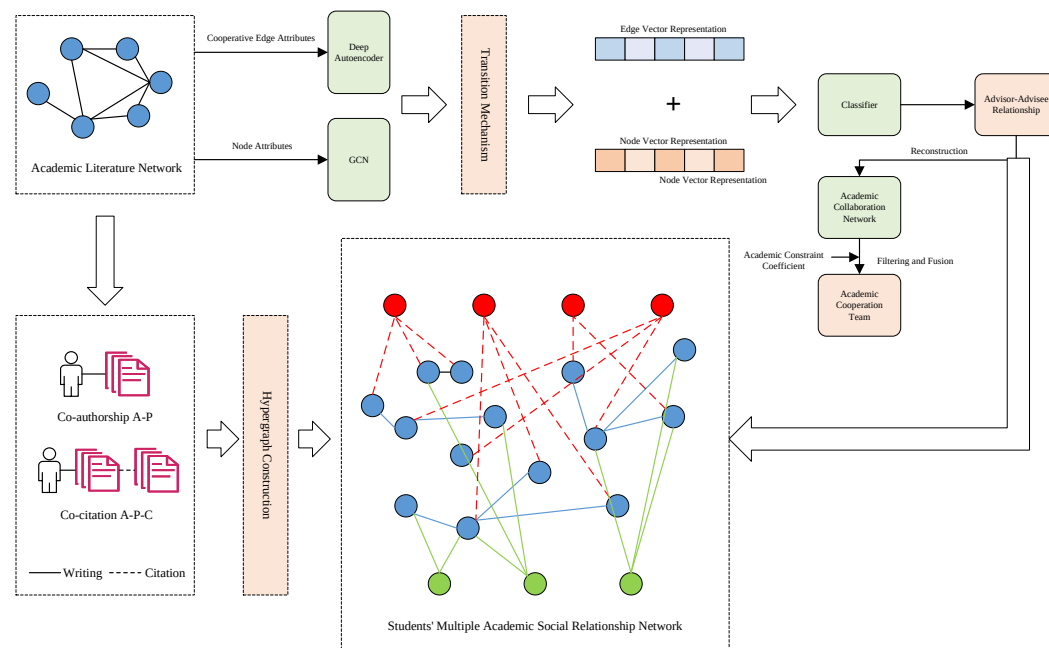


**Figure 1.** The overall framework for constructing students' multiple academic social relationship networks.

#### 4.1. High-Order Social Relationship Extraction through Co-Authorship and Co-Citation among Students

Conventional methodologies in academic social recommendation have predominantly modeled scholarly interactions as binary networks, simplifying complex academic relationships to mere pairwise connections. This approach overlooks the multifaceted nature of scholarly networks, particularly the nuanced higher-order relationships, such as co-authorship and co-citation, which are pivotal in understanding the academic landscape.

Addressing this limitation, the present research introduces a novel framework by constructing a hypergraph on a diverse academic literature network, denoted as  $G$ . This framework aims to capture and articulate higher-order social dynamics among scholars, focusing on the intricate patterns of co-authorship and co-citation. These high-order interactions are defined as the joint authorship of academic papers and the mutual citation of works, respectively. By leveraging the heterogeneous nature of the academic literature network  $G$ , the study delineates these sophisticated social connections through specific meta-paths:  $A \xrightarrow{D^1} P$  for co-authorship and  $A \xrightarrow{D^1} P \xrightarrow{D^2} C$  for co-citation, leading to the establishment of dedicated networks for these relationships.

In traditional graph theory, an edge represents a connection between two nodes, which proves insufficient for encapsulating complex scholarly interactions. In contrast, the hypergraph model extends this concept, allowing a hyperedge to encompass multiple nodes. This extension is critical for accurately representing the elaborate web of high-order academic relationships. Utilizing the constructed networks for co-authorship and

co-citation, and adhering to definitions outlined in the study, the research constructs two hypergraphs to model these relationships. These relationships are quantified through incidence matrices  $H_a$  and  $H_c$ , with each matrix column representing a unique hyperedge, thereby offering a comprehensive depiction of the academic social fabric.

#### 4.2. Algorithm for Advisor–Advisee Relationship Mining Based on Network Representation Learning and Transfer Idea

To accurately identify advisor–advisee relationships within academic networks, this section introduces an algorithmic framework consisting of four main modules: Scholar Node Representation Learning, Collaborative Edge Representation Learning, Transfer Mechanism, and Advisor–Advisee Relationship Identification. Initially, the Scholar Node Representation Learning module captures characteristic information related to each scholar node, establishing a foundation for understanding collaborative relationships among scholars. Subsequently, the Collaborative Edge Representation Learning module refines these node representations, encoding the collaboration information between scholars into the edge representations. These node and edge representations are then utilized by the Transfer Mechanism, which employs transfer learning techniques to further precisely adjust and capture the complex information embedded within the network. Finally, the Advisor–Advisee Relationship Identification module integrates the prior relationships as low-dimensional embeddings, employing a supervised classifier to determine advisor–advisee connections.

##### 4.2.1. Scholar Node Representation Learning

The academic collaboration network  $G_c = (V, E_c)$  is established on the basis of the “writing” interaction among scholars within the academic literature network  $G$ , where each node  $v \in V$  symbolizes a scholar, and each edge  $e \in E_c$  signifies a co-authorship link between scholars. This study employs the adjacency matrix  $A_c \in \mathbb{R}^{|V| \times |V|}$  to depict the structure of the academic collaboration network, alongside the matrix  $A_n \in \mathbb{R}^{|V| \times f}$  to encapsulate the attribute data of all scholar nodes within the network, where for any scholars  $v_i \in V$  and  $v_j \in V$ ,  $A_{ij}^c = 1$  if  $(v_i, v_j) \in E_c$ , otherwise  $A_{ij}^c = 0$ , with  $f$  representing the attribute types of scholar nodes. Additionally, to encompass the nodes’ inherent information along with their neighborhood data in the representation generation process, this study integrates self-loops within the adjacency matrix  $A_c$ , that is, setting all diagonal elements of  $A_c$  to 1.

In the realm of the academic collaboration network, node attributes delineate the intrinsic qualities of scholar nodes, which, coupled with the network’s topological characteristics, serve as vital indicators of the network’s attributes. To adeptly model the collaboration dynamics among scholars, our advisor–advisee relationship identification framework initially assimilates both the academic and structural information of scholar nodes within the network to derive their vector representations. The node attribute matrix  $A_n$  encompasses scholar attribute features as delineated in Table 1, primarily consisting of feature labels and their descriptions.

**Table 1.** Node attribute feature descriptions.

| Feature Label | Description                              |
|---------------|------------------------------------------|
| $aa_i$        | Academic tenure of scholar $i$           |
| $pn_i$        | Total publications of scholar $i$        |
| $cn_i$        | Cumulative citation count of scholar $i$ |
| $hi_i$        | H-index of scholar $i$                   |
| $sa_i$        | Affiliated institution of scholar $i$    |
| $sr_i$        | Research focus of scholar $i$            |

The paper elaborates on several critical features as follows:

1. **Scholar Academic Tenure.** Defined by  $aa_i = y_l - y_f + 1$ , where  $y_l$  and  $y_f$  represent the years of the latest and first publications by scholar  $i$ , respectively, academic tenure ( $aa_i$ ) underscores the duration of scholar  $i$ 's academic contributions.
2. **Scholar's h-index.** A metric reflecting academic impact, a scholar's h-index is illustrated through the scenario where a scholar with an h-index of 6 has published at least six papers, each cited no fewer than six times. This metric is crucial in our advisor–advisee relationship identification model, which is adapted to different academic fields to account for variations in h-index norms.
3. **Institutional Affiliation.** Advisor–advisee relationship often extends within the same institutional bounds. For scholars with multiple affiliations, a binary vector  $S_a = \{s_j\}_{j=1}^{|L_a|}$  is utilized, where  $s_j = 1$  signifies the scholar's association with institution  $j$ , and  $s_j = 0$  otherwise.
4. **Research Focus.** The alignment of research interests between a mentor and their mentee is pivotal. Scholars' research domains are represented by a binary vector  $S_r = \{s_j\}_{j=1}^{|L_r|}$ , with  $s_j = 1$  indicating the scholar's engagement in research direction  $j$ , and  $s_j = 0$  otherwise.

To assimilate neighborhood and attribute information of scholar nodes within the network, this paper utilizes graph convolutional networks, deriving the scholar node embedding matrix  $A_{ne}$  as follows:

$$A_{ne} = \sigma \left( D_c^{-1/2} A_c D_c^{-1/2} A_n W_{ne} \right) \quad (1)$$

where  $D_{c_{ii}} = \sum_j A_{ij}^c$  is the diagonal degree matrix,  $W_{ne}$  is a learnable weight matrix for node embeddings, and  $\sigma$  represents the ReLU activation function.

#### 4.2.2. Collaborative Edge Representation Learning

In addition to the attributes of scholar nodes and the topological characteristics of the network, the collaborative attributes encapsulated within the edges of the academic collaboration network  $G_c = (V, E_c)$  are pivotal for comprehensively reflecting the network's dynamics. The collaboration pattern, especially between a mentor and a mentee, is uniquely profound, often exhibiting a closer connection than with other scholars. Thus, to adeptly model these scholarly collaboration relationships, our advisor–advisee relationship identification model extends its focus to encompass the collaborative attributes present on the network's edges, aiming to derive vector representations for these collaborative edges. For each edge  $e \in E_c$ , we utilize a collaborative edge attribute matrix  $A_e \in \mathbb{R}^{|E_c| \times g}$  to document its attribute features, where  $g$  denotes the count of collaborative edge attribute types (Table 2).

**Table 2.** Description of collaborative edge attribute features.

| Feature Label | Description                                                                    |
|---------------|--------------------------------------------------------------------------------|
| $ac_{ij}$     | Scholar $i$ 's academic age during collaboration with co-author $j$            |
| $ag_{ij}$     | Age disparity in academia between scholar $i$ and co-author $j$                |
| $tb_{ij}$     | Total scholarly outputs by scholar $i$ prior to collaboration with $j$         |
| $ct_{ij}$     | Frequency of collaborative works between scholar $i$ and $j$                   |
| $dt_{ij}$     | Temporal span of collaboration between scholar $i$ and co-author $j$           |
| $tfs_{ij}$    | Incidences scholar $i$ and $j$ have occupied first and second author positions |
| $tfl_{ij}$    | Incidences scholar $i$ and $j$ have been the first and last authors            |
| $kulc_{ij}$   | Collaborative similarity index between scholar $i$ and $j$                     |

Significant edge attributes are detailed as follows:

1. **Academic Age of Collaboration.** Defined as  $ac_{ij} = y_c - y_f + 1$ , where  $y_c$  and  $y_f$  denote the years of first co-authorship and initial publication by scholar  $i$ , respectively,  $ac_{ij}$  quantifies the academic tenure of  $i$  at the onset of collaboration with  $j$ .

2. **Collaborative Similarity between Co-authors.** The metric  $kulc_{ij}$  computes the collaboration affinity between scholars  $i$  and  $j$  as:

$$kulc_{ij} = \frac{pn_{ij}^2}{\left(\frac{1}{pn_i} + \frac{1}{pn_j}\right)} \quad (2)$$

where  $pn_{ij}$  denotes the aggregate co-authored publications, with  $pn_i$  and  $pn_j$  reflecting individual scholarly contributions.

To holistically capture edge-centric semantic details within the academic collaboration network, a deep autoencoder is employed for learning edge embeddings. Specifically, the collaborative edge attribute matrix  $A_e$  is processed through the autoencoder, bifurcated into encoder and decoder segments, each comprising multiple nonlinear transformation layers. The transformation is articulated as:

$$A_1^{em} = f(W_1^{em} A_e + b_1^{em}) \quad (3)$$

$$A_j^{em} = f(W_j^{em} A_{j-1}^{em} + b_j^{em}), \quad \text{for } j = 2, \dots, k \quad (4)$$

where  $k$  represents the encoder–decoder layer count,  $f$  signifies the activation function, employing tanh for edge embedding acquisition  $A_{ee} = A_{k/2}^{em}$ , and sigmoid for reconstructed edge representation  $A_{re}$ .  $W_j^{em}$  and  $b_j^{em}$  denote the linear transformation and bias for layer  $j$ , respectively. Dropout is applied to curb overfitting. The autoencoder's objective is to minimize the discrepancy between  $A_{re}$  and  $A_e$ , with loss  $L_e = \|A_e - A_{re}\|_F^2$ .

During the edge representation learning's pre-training phase, the Adaptive Moment Estimation (Adam) optimization method is utilized for fine-tuning the model parameters of the deep autoencoder. Subsequently, the model, with pre-trained weights, is further refined within our advisor–advisee relationship identification framework to enhance its predictive performance.

#### 4.2.3. Transfer Mechanism

In the endeavor to unravel advisor–advisee relationship dynamics within academic collaboration networks, this study integrates network representation learning techniques to dissect node attributes, network architecture, and edge characteristics, thereby capturing the intricate information embedded within. Nevertheless, the interactions among academic nodes often harbor diverse and rich semantic nuances, necessitating their incorporation into the holistic modeling of academic collaborations. Drawing inspiration from transfer mechanisms employed in graph embedding algorithms for knowledge graphs, this investigation adopts a similar approach in the semantic realm of advisor–advisee relationships to encapsulate interactions between scholars, thereby refining the embeddings of both nodes and edges. Specifically, it envisions advisor–advisee relationship transfer, facilitating the translation of student node embeddings towards their mentor counterparts within the advisor–advisee relationship semantic space, leveraged through the collaborative edge embeddings to refine the node and edge representations.

In knowledge graph embedding algorithms, the transfer concept interprets a relation in a triplet (head entity, relation, tail entity) as a vector translation from the head entity to the tail entity, aiming for proximity in the representation space post-transfer. Analogously, in mentorship contexts, the student (advisee) representation augmented by a mentorship relationship vector should approximate the mentor (advisor) representation, i.e.,  $h_{advisee} + r \approx t_{advisor}$ .

However, advisor–advisee relationship models face the challenge of over-convergence due to the often one-to-many nature of mentor–student relationships. This simplistic transfer constraint may result in excessively proximal representations for students sharing a mentor, blurring semantic distinctiveness.

To circumvent this, inspired by advancements in transfer mechanisms within knowledge graph embeddings, this paper initiates with a feature transformation on scholar node representations prior to transfer operations. By mapping these representations to the advisor–advisee relationship’s semantic vector space before the transfer, the study addresses disparities in the feature space between node and edge embeddings and mitigates the over-convergence quandary in advisor–advisee relationship learning.

Echoing strategies from related research on transfer mechanisms in knowledge graph embeddings, this study posits that interactions among academic nodes can be construed as vector translations within the advisor–advisee representation space.

For any scholarly pair  $(i, j)$  within the academic network exhibiting a collaborative link, the paper first transforms their node representations into the advisor–advisee relationship’s semantic vector space:

$$A_i^{trn} = \sigma(W^{tr} \cdot A_i^{ne} + b^{tr}) \quad (5)$$

$$A_j^{trn} = \sigma(W^{tr} \cdot A_j^{ne} + b^{tr}) \quad (6)$$

where  $\sigma$  denotes the activation function,  $W^{tr}$  the feature transformation matrix, and  $b^{tr}$  the bias vector.

Acknowledging the advisor–advisee relationship’s inherent directionality, the model adjusts scholar node and edge embeddings by leveraging the transfer mechanism, predicated on collaborative edge embeddings. For scholarly pairs in advisor–advisee relationship linkage, their node embeddings should converge based on the edge embeddings; for those without such linkage, divergence is expected. The optimization criterion of this transfer mechanism, hence, seeks to minimize the loss function  $L_{tr}$ :

$$L_{tr} = \sum \max(\gamma + d(A_i^{trn} + A_{ij}^{ee}, A_j^{trn}) - d(A_i^{trn} + A_{ij}^{ee}, A_k^{trn}), 0) \quad (7)$$

Here,  $\gamma$  is a margin hyperparameter exceeding zero ( $\gamma > 0$ ), and  $(i, j)$  signifies a negative sample derived via negative sampling for the mentor–mentee dyad  $(i, j)$ , employing random substitution of either node to generate a collaboratively linked but non-advisor–advisee relationship pair. The distance function  $d$  employs Euclidean metrics to gauge proximity.

#### 4.2.4. Advisor–Advisee Relationship Identification

Upon mastering the node representations  $A_{trn}$  and edge representations  $A_{ee}$ , this study proceeds to model the intricate tapestry of academic collaborations within the network  $G_c = (V, E_c)$ , aiming to distill these relationships into low-dimensional embeddings. Subsequently, a supervised classifier discerns the presence of advisor–advisee connections between collaborating scholars  $v_i \in V$  and  $v_j \in V$ , represented by an edge  $e \in E_c$ .

To refine the identification of mentor–student dyads amidst these scholarly collaborations, the network undergoes a filtration process, excluding pairs less likely to embody advisor–advisee relationship roles. This selective sieve, inspired by the academic tenure hypothesis posited by Wang et al. [23], posits that mentors generally boast a longer academic tenure than their mentees. Utilizing this criterion, the paper meticulously sifts through the network, excising improbable mentor–mentee linkages to forge a refined set of candidate pairs  $E_{cc}$  earmarked for advisor–advisee relationship scrutiny. Upon successful classification, the specific mentor–student roles within these dyads are also ascertained.

Employing logistic regression, the paper crafts a supervised classification model, articulated through the loss function:

$$L_{lr} = \sum_{(i,j) \in E_{cc}} (L_{lij} - \sigma(A_{ijce} \cdot W_{lr} + B_{lr}))^2 \quad (8)$$

Here,  $\sigma$  signifies the sigmoid activation function,  $L_{lij}$  denotes the authentic advisor–advisee relationship label between scholars  $i$  and  $j$ , and  $A_{ce}$  encapsulates the amalgamation

of node and edge representations, i.e.,  $A_{ijce} = A_{itrn} \parallel A_{ijee} \parallel A_{jtrn}$ . The parameters  $W_{lr}$  and  $B_{lr}$  represent the logistic regression's weight matrix and bias vector, respectively.

Converging towards an optimal model fidelity, the study introduces a composite loss function  $L_{aai}$ , formulated as:

$$L_{aai} = \alpha L_e + \beta L_{tr} + L_{lr} + \gamma L_{reg} \quad (9)$$

with  $\alpha$ ,  $\beta$ , and  $\gamma$  serving as hyperparameters to balance the contribution of each model component. The regularization term  $L_{reg}$ , aimed at mitigating overfitting, is defined as:

$$L_{reg} = \sum (W_{ne}^2 + W_{em}^2 + b_{em}^2 + W_{tr}^2 + b_{tr}^2 + W_{lr}^2 + B_{lr}^2) \quad (10)$$

to ensure model robustness. The overarching ambition of the advisor–advisee relationship identification model, fueled by the transfer mechanism, pivots on minimizing  $L_{aai}$  through the backpropagation algorithm, leveraging stochastic gradient descent (SGD) for optimization.

#### 4.3. Identification of Academic Collaboration Teams via Cooperation Strength

In the evolving landscape of the natural sciences, characterized by increasing diversification and intersectionality, team-based research has become an indispensable paradigm in educational innovation. This paradigm shift, aiming to enhance research quality and efficiency, pivots from solitary scholarly endeavors to collaborative academic research teams. Such teams facilitate rapid knowledge dissemination and problem-solving through cohesive cooperation, often comprising several core units centered around mentor–mentee dynamics, fostering intimate collaborative bonds.

Leveraging insights from previously delineated mentor–mentee social networks, this investigation further delineates the structure of academic teams, mirroring the distinctive academic trajectories of students within the broader academic collaboration network. This methodology entails constructing a team collaboration network, recalibrating it based on collaboration intensity, and thereby identifying distinct academic teams.

Initiating this process, a team collaboration network  $G_{TC} = (V_T, E_{TC})$  is established upon the academic collaboration network  $G_c$ . This network,  $G_{TC}$ , emerges from co-authorship dynamics among core team constituents, aimed at discerning academic teams. Herein, each node  $v \in V_T$  represents a core team, encapsulated around a mentor–mentee nexus with student memberships, while each edge  $e \in E_{TC}$  delineates collaborative interconnections between these core units.

To intricately assess the collaboration strength between core teams, an index is utilized to assign weights to the edges  $e \in E_{TC}$  within  $G_{TC}$ , transforming it into a weighted network  $G_{TC} = (V_T, E_{TC}, W_{TC})$ . Among various indices to evaluate collaborative vigor, such as CF and CI, this study adopts the Collaboration Intensity Index (CII) [21] for quantifying team collaboration strength within the network. The collaboration intensity index  $CII_{ij}$  between two core teams  $i$  and  $j$  is computed as:

$$CII_{ij} = \frac{\Delta t_{ij}^2}{\Delta t_i \times \Delta t_j} \quad (11)$$

where  $\Delta t_i$  and  $\Delta t_j$  denote the publication outputs of teams  $i$  and  $j$  within the network's temporal bounds, respectively, and  $\Delta t_{ij}$  signifies the shared publications by teams  $i$  and  $j$  over the same timeframe. A heightened  $CII$  suggests a denser collaborative link, while a diminished  $CII$  indicates a more tenuous connection. By evaluating the  $CII$  across all edges  $e \in E_{TC}$ , the paper recalibrates  $G_{TC}$ 's edges, rendering a network reweighted by  $CII$ .

Conclusively, recognizing that extensive academic collaboration teams typically revolve around multiple core teams bound by stringent cooperative links, this study amalgamates closely knit core teams by filtering edges within  $G_{TC}$ , thus pinpointing the academic teams students affiliate with. A distinct academic relationship constraint coefficient  $\omega$  filters

through  $G_{TC}$ , delineating academic teams. For each edge  $e \in E_{TC}$  within  $G_{TC}$ , edges below  $\omega$  denote loose collaborations, whereas those surpassing  $\omega$  signify tight collaborations. This filtration, premised on the notion that 20% of relationships in social networks are strong and 80% are weak [44], sets  $\omega$  at the minimum edge weight within the top 20% by weight in  $G_{TC}$ . This method merges core teams exhibiting close collaborative ties within  $G_{TC}$ , thus definitively identifying student-associated academic teams. Additionally, this exploration harnesses hypergraphs for encoding these academic teams, culminating in the portrayal of a multifaceted academic social network of students.

#### 4.4. Augmenting Student Representation Learning via Social Interactions

Addressing the challenges of the “Academic Big Data Era”, we introduce a self-supervised social recommendation model for academic papers, designed to tackle information overload. This model enhances recommendation quality by leveraging advanced embeddings for students and papers, thus minimizing reliance on sparse interactions. It focuses on three main aspects: improved student representation, comprehensive paper embedding, and model optimization. This approach aims for precise preference identification and enhanced recommendation performance, facilitating a deeper understanding of its components and interactions, as depicted in Figure 2.

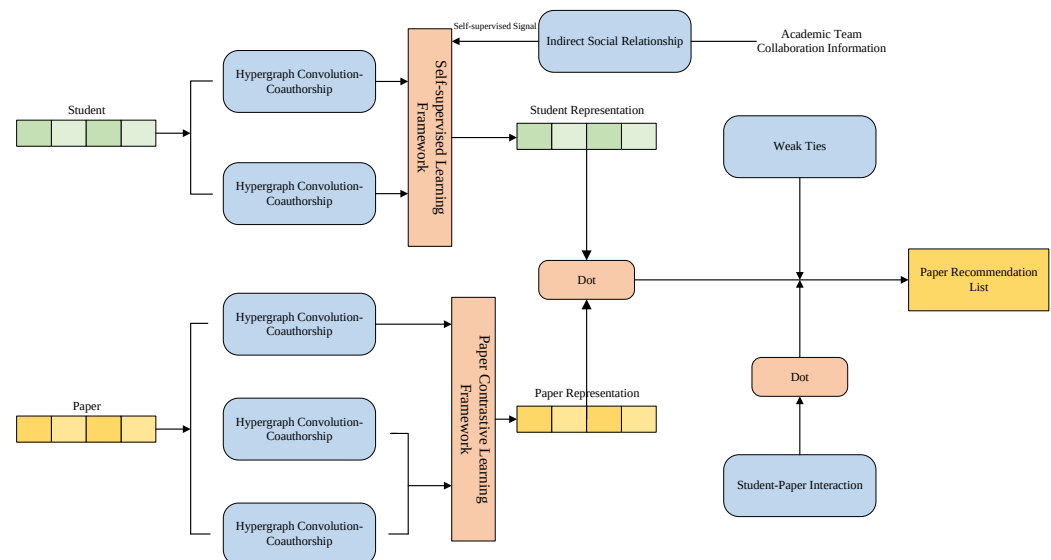


**Figure 2.** The self-supervised academic paper social recommendation framework for students: an overview of constructing multifaceted academic social relationships among students.

##### 4.4.1. Hypergraph-Based Learning of High-Order Social Interactions

Leveraging the intricate multi-relational academic social network outlined in Section 4, this segment endeavors to harness the wealth of social interactions therein to derive comprehensive student embeddings. As elucidated in Section 4.1, for encapsulating the complex social interplays amongst scholars within the heterogeneous academic literature network  $G$ , this study erects hypergraphs centered around two pivotal higher-order academic social dynamics: co-authorship and co-citation. These dynamics are quantitatively captured through the incidence matrices  $H_a$  and  $H_c$ , respectively, laying the groundwork for two distinct hypergraphs to represent these sophisticated social interactions.

This discourse further explores the application of hypergraph convolutional neural networks (HCNNs) to encode the high-order structural data embodied within student representations corresponding to the aforementioned hypergraphs. Mirroring the encoding stratagem of graph convolutional networks (GCNs) yet tailored for hypergraph structures, HCNNs employ a dual-phase transformation mechanism—node to hyperedge and hy-

peredge back to node—to aptly encapsulate the original hypergraph formation and its high-order neighborhood essence. The operational formulae are delineated as follows:

$$Q_a^{l+1} = \sigma \left( D_a^{-\frac{1}{2}} H_a L_a^{-1} H_a^T Q_a^l W_a \right) \quad (12)$$

$$Q_c^{l+1} = \sigma \left( D_c^{-\frac{1}{2}} H_c L_c^{-1} H_c^T Q_c^l W_c \right) \quad (13)$$

where  $Q_a^{l+1}$  and  $Q_c^{l+1}$  epitomize the student embeddings at the  $l + 1$  layer for co-authorship and co-citation hypergraphs, respectively, with  $\sigma$  representing the ReLU activation function.  $D_a, D_c, L_a, L_c$ , along with  $W_a, W_c$ , signify the vertex diagonal matrices, hyperedge diagonal matrices, and the trainable parameter matrices corresponding to the co-authorship and co-citation hypergraphs, respectively.

Consequent to  $L$  layers of information propagation and refinement, the student embeddings from each layer are aggregated to yield the final embeddings tailored to the high-order social constructs of co-authorship and co-citation, denoted as  $Q_a$  and  $Q_c$ , respectively. The amalgamation is executed as follows:

$$Q_a = \frac{1}{L+1} \sum_{l=0}^L Q_a^l \quad (14)$$

$$Q_c = \frac{1}{L+1} \sum_{l=0}^L Q_c^l \quad (15)$$

initiating with  $Q_a^0 = Q_c^0$  through a process of random initialization.

#### 4.4.2. Cross-Relationship Contrast for Enhanced Student Representation Learning

Veering from conventional self-supervised methodologies that juxtapose original and altered networks for contrastive learning, this segment introduces a novel “cross-relationship contrast” learning paradigm. This innovative framework exploits the symbiotic supervision inherent between two distinct high-order social structures, “co-authorship” and “co-citation”. It is further augmented by a self-supervised signal, rooted in an original sample selection strategy meticulously crafted for this study. Such an approach facilitates the autonomous derivation of student embeddings that are both comprehensive and reflective of the nuanced, multifaceted academic social network landscape.

The pivotal role of positive and negative sample construction in augmenting representation quality within contrastive self-supervised learning is well documented. Prior to delving into the “cross-relationship contrast” framework, an exploration of the mechanism for delineating positive and negative samples is paramount. Traditional methods frequently enlist random sampling or subgraph alterations for sample generation, potentially underutilizing the contrastive learning paradigm’s full potential, especially in recommendation contexts. This predicament prompts the introduction of a novel sample selection strategy that, diverging from conventional methodologies, pivots on indirect social relationships derived from academic collaboration teams. This approach notably diminishes the impact of noise on representation fidelity by integrating context from authentic academic team collaborations.

This strategy succinctly compacts the interaction network spanning team members and academic publications within academic teams into a focused internal student collaboration network  $G_{ac} = (V_{ac}, E_{ac}, W_{ac})$ . Here, each node  $v \in V_{ac} \subset A_t$  epitomizes a team member (mentors excluded due to their expansive research domains potentially diluting indirect social relationship accuracy and student representation learning quality). An edge  $e \in E_{ac}$  signifies at least one joint paper interaction, with  $W_{ac}$  quantifying the shared publications. The adjacency matrix  $A_{ac} \in \mathbb{R}^{|V_{ac}| \times |V_{ac}|}$  embodies the network’s graphical structure.

Utilizing the Louvain method, a renowned community detection algorithm based on topological configurations, the internal student collaboration network  $G_{ac}$  facilitates the revelation of students within academic teams sharing analogous learning dispositions and preferences, thereby uncovering latent social interconnections among team members.

Leveraging these unearthed indirect social ties within academic teams, a “cross-relationship contrast” sample selection modality is formulated, defining positive  $\mathcal{P}$  and negative  $\mathcal{N}$  sample cohorts for the contrastive learning schema. For any student node  $i$ , team members linked via indirect social channels are deemed positive samples, encapsulated as  $\mathcal{P}_i$ , whereas all remaining team members are categorized as negative samples,  $\mathcal{N}_i$ . Furthermore, for student nodes  $i$  devoid of historical academic paper interactions, core team members are ascribed as positive samples  $\mathcal{P}_i$ , with all other students allocated to negative samples  $\mathcal{N}_i$ , thus enabling recommendations in scenarios typified by sparse data.

With the delineation of positive  $\mathcal{P}_i$  and negative  $\mathcal{N}_i$  samples for student node  $i$ , their embeddings, specifically tailored to the “co-authorship” and “co-citation” high-order social structures,  $Q_i^a$  and  $Q_i^c$ , respectively, are assimilated into the contrastive learning schema. The contrast loss for the “co-authorship” perspective is articulated as:

$$L_i^a = -\log \frac{\sum_{j \in \mathcal{P}_i} \exp(\text{sim}(Q_i^a, Q_j^a)/\tau)}{\sum_{k \in \{\mathcal{P}_i \cup \mathcal{N}_i\}} \exp(\text{sim}(Q_i^a, Q_k^a)/\tau)} \quad (16)$$

Here,  $\text{sim}()$  computes the cosine similarity between vector pairs, with  $\tau$  denoting a temperature hyperparameter. This framework, diverging from the norm, encompasses multiple positive samples. For any sample duo, the target embedding within our “co-authorship” purview originates from the “co-authorship” domain, whereas the comparative positive and negative samples derive from the “co-citation” sphere.

Analogously, the contrast loss from the “co-citation” standpoint is evaluated as:

$$L_i^c = -\log \frac{\sum_{j \in \mathcal{P}_i} \exp(\text{sim}(Q_i^c, Q_j^c)/\tau)}{\sum_{k \in \{\mathcal{P}_i \cup \mathcal{N}_i\}} \exp(\text{sim}(Q_i^c, Q_k^c)/\tau)} \quad (17)$$

In this scenario, for a given sample pair, the target embedding in our contrastive learning framework originates from the “co-citation” perspective, with the embeddings for positive and negative samples derived from the “co-authorship” perspective.

The aggregate loss for our “cross-relationship contrast” learning framework is formalized as:

$$L_{st} = \frac{1}{|\mathcal{A}_t|} \sum_{i \in \mathcal{A}_t} [\epsilon L_i^a + (1 - \epsilon) L_i^c] \quad (18)$$

where  $\epsilon$  is a hyperparameter that balances the contribution of the two perspectives. In our experiments, the embedding  $Q^a$  from the “co-authorship” perspective is utilized for the recommendation task as it is presumed to preserve social information pertinent to the academic environment more effectively than the “co-citation” perspective.

Through this method, the study innovatively leverages cross-relationship contrastive learning to enrich the learning of student representations by intertwining the embeddings of student nodes from both “co-authorship” and “co-citation” high-order social structures. This original “cross-relationship contrast” strategy not only fosters a deeper comprehension of student social connections within the intricate academic social network but also introduces a novel approach to addressing the cold-start problem in recommendation tasks.

#### 4.5. Self-Supervised Academic Paper Representation Learning

##### 4.5.1. Learning Local Citation Relationships

Within the multifaceted realm of the heterogeneous academic literature network, a plethora of entity types and multi-faceted interaction relationships coexist, positioning papers as a pivotal explicit node type instrumental in delineating student preferences. This segment endeavors to encapsulate the comprehensive information and intricate interaction

dynamics of paper nodes. It aims to autonomously derive detailed academic paper embeddings for recommendation objectives. Central to the paper recommendation schema, the paper citation network, denoted as  $\mathcal{G}_{CI} = \{P, E_{CI}\}$ , is a derivative subgraph of the broader heterogeneous academic literature network  $\mathcal{G}$ , predicated on paper nodes and citation linkages. In this construct, each edge  $e \in E_{CI}$  embodies a citation linkage between pairs of paper nodes. Given the non-discriminatory nature of citing versus cited dynamics,  $\mathcal{G}_{CI}$  is modeled as an undirected graph.

To distill local neighborhood connections of papers, a single-layer graph convolutional neural network (GCN) is harnessed, capitalizing on the topological framework of the paper citation network. This approach facilitates the acquisition of local embeddings, articulated as follows:

$$S_L = \sigma \left( D_{CI}^{-\frac{1}{2}} A_{CI} D_{CI}^{-\frac{1}{2}} S_I W_L \right) \quad (19)$$

Herein,  $S_L$  delineates the resultant local embedding matrix for papers, while  $A_{CI}$  and  $D_{CI}$  refer to the adjacency and degree matrices of the paper citation network, respectively.  $S_I$ , procured through a process of random initialization, and  $W_L$ , a designated linear transformation matrix, together with  $\sigma$ , the ReLU non-linear activation function, converge to formulate the foundation for learning paper embeddings within the local citation network context.

This methodology underscores a focused effort to mine the latent semantic and structural nuances resident within academic papers, thus contributing to the nuanced recommendation framework that aligns with student academic interests and research trajectories.

#### 4.5.2. Global and Higher-Order Paper Relationship Learning

Expanding beyond the confines of local neighborhood dynamics within the paper citation network, this segment aims to encapsulate the expansive realm of global citation relationships. This endeavor supplements the paper representation learning framework with a comprehensive view of the academic landscape. Hypergraph structures, by transcending traditional graph limitations—where edges link multiple nodes—emerge as a potent tool for modeling intricate higher-order interactions. This characteristic is pivotal for representing global neighborhood affiliations amongst papers, offering a robust mechanism to capture complex interaction patterns.

A hypergraph, constructed from shared citation dynamics within the paper citation network, serves as the foundation for disseminating global insights through hyperedges. This dissemination leverages a “node-hyperedge-node” dual-phase feature transformation strategy, detailed as follows:

$$S_G^{l+1} = \sigma \left( D_G^{-\frac{1}{2}} H_G L_G^{-1} H_G^T S_G^l W_G \right) \quad (20)$$

Here,  $S_G^{l+1}$  delineates the paper embedding at iteration  $l + 1$ , refined through shared citation interactions, with  $\sigma$  representing the ReLU activation function.  $D_G$ ,  $H_G$ ,  $L_G$ , and  $W_G$  correspond to the hypergraph’s vertex diagonal matrix, incidence matrix, hyperedge diagonal matrix, and the trainable parameter matrix, respectively.

Post  $L$  iterations of global information circulation and assimilation, the ultimate global paper embedding,  $S_G$ , materializes through an averaging process across all layers:

$$S_G = \frac{1}{L+1} \sum_{l=0}^L S_G^l \quad (21)$$

Furthermore, this discourse extends to incorporate latent higher-order interaction insights amongst academic papers. Specifically, higher-order interactions, distilled through metapaths that elucidate complex patterns, such as papers “co-authored by the same scholar” and “co-cited by the same scholar”, are adeptly modeled. The encapsulation of

these higher-order interactions employs hypergraphs and their neural network counterparts, facilitating the following learning mechanism:

$$S_{ad}^{l+1} = \sigma \left( D_{ad}^{-\frac{1}{2}} H_{ad} L_{ad}^{-1} H_{ad}^T S_{ad}^l W_{ad} \right) \quad (22)$$

$$S_{cd}^{l+1} = \sigma \left( D_{cd}^{-\frac{1}{2}} H_{cd} L_{cd}^{-1} H_{cd}^T S_{cd}^l W_{cd} \right) \quad (23)$$

$S_{ad}^{l+1}$  and  $S_{cd}^{l+1}$  encapsulate the embeddings for distinct high-order interactions at iteration  $l + 1$ , with  $H_{ad}$ ,  $H_{cd}$ ,  $D_{ad}$ ,  $D_{cd}$ ,  $L_{ad}$ ,  $L_{cd}$ ,  $W_{ad}$  and  $W_{cd}$  representing the respective incidence matrices, vertex diagonal matrices, hyperedge diagonal matrices, and trainable parameter matrices for the two hypergraphs.

Concluding after  $L$  propagation cycles, the final representations for higher-order interactions,  $S_{ad}$  and  $S_{cd}$ , are ascertained as:

$$S_{ad} = \frac{1}{L+1} \sum_{l=0}^L S_{ad}^l \quad (24)$$

$$S_{cd} = \frac{1}{L+1} \sum_{l=0}^L S_{cd}^l \quad (25)$$

#### 4.5.3. Local High-Order Contrastive Learning for Papers

This final segment introduces a contrastive learning architecture specifically tailored for academic papers, utilizing supervision signals from both global and local perspectives. This novel approach orchestrates a self-contrast between local representations and their global, higher-order counterparts, aiming to distill comprehensive paper representations. These representations encapsulate the dense web of complex interactions within the heterogeneous academic literature network. In this framework, positive sample pairs are constituted by identical paper nodes viewed through different lenses, while disparate paper nodes within the same views act as negative samples. The formula for calculating the overall loss in this paper contrastive learning architecture is articulated as:

$$L_{sp} = \frac{1}{|\mathcal{P}|} \sum_{i \in \mathcal{P}} -\log \frac{\exp(\text{sim}(S_i^L, S_i^G)/\tau) + \exp(\text{sim}(S_i^L, S_i^{ad})/\tau) + \exp(\text{sim}(S_i^L, S_i^{cd})/\tau)}{\sum_{k \in \mathcal{P}} [\exp(\text{sim}(S_i^L, S_k^G)/\tau) + \exp(\text{sim}(S_i^L, S_k^{ad})/\tau) + \exp(\text{sim}(S_i^L, S_k^{cd})/\tau)]} \quad (26)$$

where  $\text{sim}()$  calculates the cosine similarity between vector pairs, and  $\tau$  is a temperature parameter moderating the similarity measure.

#### 4.6. Model Optimization

The preceding discussion has centered around the application of unsupervised, self-supervised signals for capturing both semantic and structural nuances within the network. This facilitated the learning of enriched representations for students and academic papers alike. Nonetheless, the essence of recommendation inherently intertwines with the interaction data between students and papers. Thus, a pairwise learning approach is adopted for optimizing the model within the academic paper top-k recommendation task. This approach not only steers the parameter learning but also refines the embedding learning trajectory.

To align student and paper representations within a unified vector space, the following mappings are employed:

$$q_i = \sigma(W_Q \cdot Q_i^a + b_Q) \quad (27)$$

$$s_j = \sigma(W_S \cdot S_j^L + b_S) \quad (28)$$

where  $\sigma$  signifies the ReLU activation function.  $W_Q$ ,  $W_S$ ,  $b_Q$ , and  $b_S$  represent the transformation matrices and bias vectors responsible for transmuting student and paper feature representations, respectively.

The model's optimization leverages a pairwise learning strategy, predicated on the axiom that observed interactions ought to rank above non-observed ones:

$$L_O = \sum_{(i,j,k) \in T_S} (\hat{r}_{ij} - \hat{r}_{ik} - 1)^2 \quad (29)$$

Here,  $T_S$  is the training dataset, with each triplet  $(i, j, k) \in T_S$  incorporating a student  $at_i \in A_t$ , an interacted academic paper  $p_j \in P$  as a positive example, and a non-interacted academic paper  $p_k \in P$  serving as a negative instance.  $\hat{r}_{ij} = q_i^T s_j$  delineates the predicted affinity score between student  $at_i$  and paper  $p_j$ .

Subsequently, the self-supervised frameworks for both students and papers are amalgamated with the main recommendation task's objective for holistic optimization. The comprehensive objective function is formulated as:

$$L = L_O + \delta(L_{st} + L_{sp}) + \lambda \|\Phi\|_2^2 \quad (30)$$

In this equation,  $\delta$  is a balancing hyperparameter for the self-supervised learning component,  $\Phi$  encompasses the parameters engaged in the recommendation mechanism, and  $\lambda$  is the regularization term.

Building on the CBCS methodology [45] to streamline model computation and elevate recommendation efficacy, this study initially narrows down a candidate paper set for recommendations. Instead of evaluating the entire paper corpus, the recommendation process focuses on a select set of candidate papers, identified through indirect social ties and shared preferences within academic teams, enhancing recommendation diversity. This approach utilizes the CBCS method's principle, where if a user has interacted with any item in another user's item set, a weak tie is inferred between these two users. Utilizing these weak ties, the CBCS method narrows down a candidate item set for recommendations. Similarly, this study extends the concept of weak ties to include indirect social relationships within academic teams, identifying candidate scholar sets based on similar preferences discovered in previous sections. Consequently, papers associated with the candidate scholar set form the basis for generating a candidate set for student recommendations. The final top-k academic paper recommendations are then derived from this candidate set, optimizing both the model's efficiency and the diversity of its recommendations.

## 5. Experiment

### 5.1. Experimental Datasets and Preprocessing

#### 5.1.1. Experimental Datasets

This study employs the Aminer dataset [46], a comprehensive repository of academic publications meticulously compiled by Professor Tang and his team at Tsinghua University. Encompassing a wide array of academic disciplines, the Aminer dataset features 2,092,356 academic papers, 8,024,869 citation links, 1,712,433 authors, and 4,258,615 co-authorship instances. The dataset is publicly accessible via <https://www.aminer.cn/aminernetwork> (accessed on February 2024).

Due to the extensive scope of the original Aminer dataset, a curated subset was selected for the experimental evaluation and analyses conducted within this study. Furthermore, to ascertain the efficacy of the proposed mentor–mentee relationship identification model and to facilitate subsequent academic paper recommendation experiments for students, authentic mentor–mentee relationship pairs are necessitated. To this end, the most recent version of the Academic Family Tree (AFT) dataset [47], harvested from <https://academicfamilytree.org/> (accessed on February 2024), serves as a vital resource. The AFT project, a dynamic, crowd-sourced endeavor, chronicles veritable academic genealogies

spanning 73 disciplines. Table 3 delineates the statistical particulars of select research domains within the AFT dataset, distinguished by their data richness.

**Table 3.** Statistical data for select domains in the AFT dataset.

| Research Field       | Number of Scholars | Number of Advisor–Advisee Relationship Relations |
|----------------------|--------------------|--------------------------------------------------|
| Physics              | 54,916             | 58,875                                           |
| Chemistry            | 117,000            | 136,536                                          |
| Neuroscience         | 142,531            | 170,879                                          |
| Education            | 56,966             | 49,925                                           |
| Sociology            | 23,429             | 18,413                                           |
| Economics            | 22,088             | 18,414                                           |
| Anthropology         | 11,688             | 10,280                                           |
| Microbiology         | 17,297             | 14,861                                           |
| Nursing              | 13,138             | 10,764                                           |
| Political Science    | 16,428             | 13,539                                           |
| Literature           | 26,012             | 19,713                                           |
| Computer Science     | 23,678             | 18,866                                           |
| Theology             | 15,443             | 12,754                                           |
| Mathematics          | 35,551             | 29,767                                           |
| Evolutionary Biology | 14,574             | 18,417                                           |

### 5.1.2. Data Preprocessing

Prior to the deployment of the Aminer and AFT datasets in our experimental framework, two pivotal challenges necessitate resolution: dataset alignment and the heterogeneity across disciplines. Aminer and AFT, while independent datasets, must be cohesively aligned for our analysis, given our requirement for an integrated academic publication dataset that encompasses mentor–mentee relationships from AFT for downstream experimentation. Moreover, [48,49] suggests that collaboration patterns among students and mentors vary distinctly across fields, potentially influencing model efficacy. Consequently, our experimental design entails discipline-specific evaluations to gauge both the effectiveness and universality of the proposed model.

In the preprocessing phase, real mentor–mentee relationship pairs from the AFT dataset, spanning the years 2000 to 2015, are meticulously extracted and subsequently aligned with the corresponding entities in the Aminer dataset. Notably, the Aminer dataset is preprocessed to address author name disambiguation, thereby facilitating the straightforward identification of scholars and their real-world identities.

The alignment process unfolds in two stages: initially, scholar names constituting real mentor–mentee pairs from 2000 to 2015 are harvested from the AFT dataset, specifically targeting the research domains outlined in Table 3. Concurrently, author names are extracted from co-authorship instances within the Aminer dataset, with the scholar names then rendered through regular expressions for standardization. Subsequently, scholar pairs from AFT are paired with their counterparts in Aminer. During this pairing process, a co-author duo from Aminer is recognized as a bona fide mentor–mentee pair solely if an exact match of scholar names is established across both datasets, thereby affirming the integrity of the alignment outcomes.

This rigorous preprocessing and alignment exercise across various disciplines culminates in the acquisition of authentic mentor–mentee relationship pairs for our experimental endeavors, culminating in a rich dataset of academic publications replete with verifiable mentor–mentee dynamics. Table 4 delineates the statistical specifics of the leading fields, as determined by the volume of successfully matched mentor–mentee pairs.

**Table 4.** Statistical data for the Aminer and AFT dataset matching results in select domains.

| Research Field   | Number of Advisor–Advisee Relationship Pairs | Time Range |
|------------------|----------------------------------------------|------------|
| Computer Science | 10,652                                       | 2000–2015  |
| Neuroscience     | 5028                                         | 2000–2015  |
| Mathematics      | 4773                                         | 2000–2015  |
| Chemistry        | 2957                                         | 2000–2015  |
| Physics          | 1452                                         | 2000–2015  |
| Education        | 1029                                         | 2000–2015  |

### 5.2. Experiments on Mentor–Mentee Relationship Identification Model

This section presents experiments and analyses of the mentor–mentee relationship identification model proposed in Section 4.2, aiming to demonstrate its effectiveness and universality. It encompasses evaluation metrics, comparison methods, and results analysis.

#### 5.2.1. Evaluation Metrics and Comparison Methods

The advisor–advisee relationship mining issue is considered a binary classification problem, focusing on predicting whether a scholar  $i$  is the mentor of scholar  $j$ . To evaluate the performance of our mentor–mentee relationship identification model (NTARM), four widely used metrics are selected: precision, recall, accuracy, and F1-score, calculated as follows:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (31)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (32)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (33)$$

$$F1\text{-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (34)$$

where  $TP$  (True Positive) is the count of correctly predicted positive relationships;  $TN$  (True Negative), the count of correctly predicted negative relationships;  $FP$  (False Positive), the count of negative relationships predicted as positive; and  $FN$  (False Negative), the count of positive relationships predicted as negative.

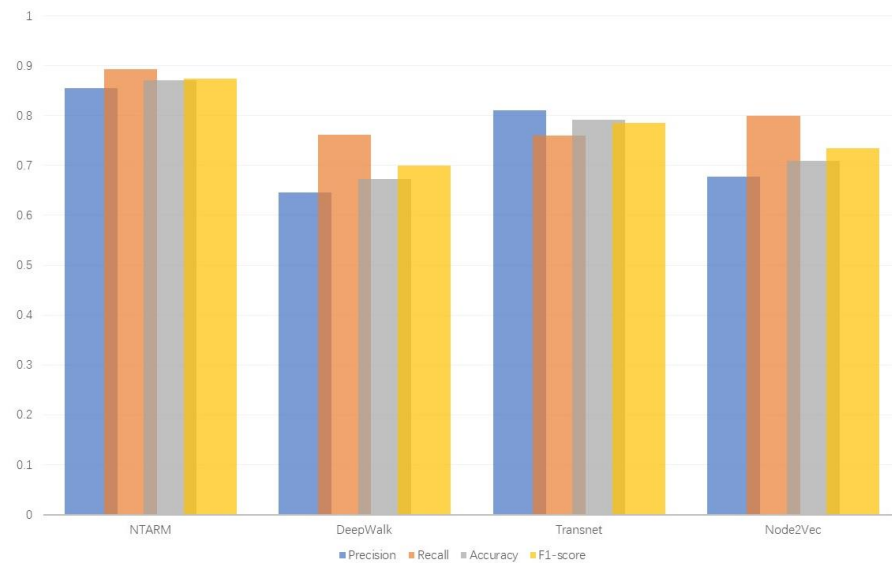
Furthermore, our model is compared against the following network representation learning and existing mentor–mentee relationship identification methods:

- DeepWalk [50], which uses random walks to obtain network locality information and skip-gram for vertex latent representation learning.
- Node2vec [51], a semi-supervised algorithm that balances homophily and structural equivalence in embeddings through controllable search bias.
- TransNet [52], a network representation learning model based on transition mechanisms.
- Shifu [25], a deep learning-based advisor–advisee relationship identification method considering both local attributes and network structural features of scholars.
- Shifu2 [53], which, besides considering network structural features, also accounts for semantic information of scholar nodes and collaboration edges.

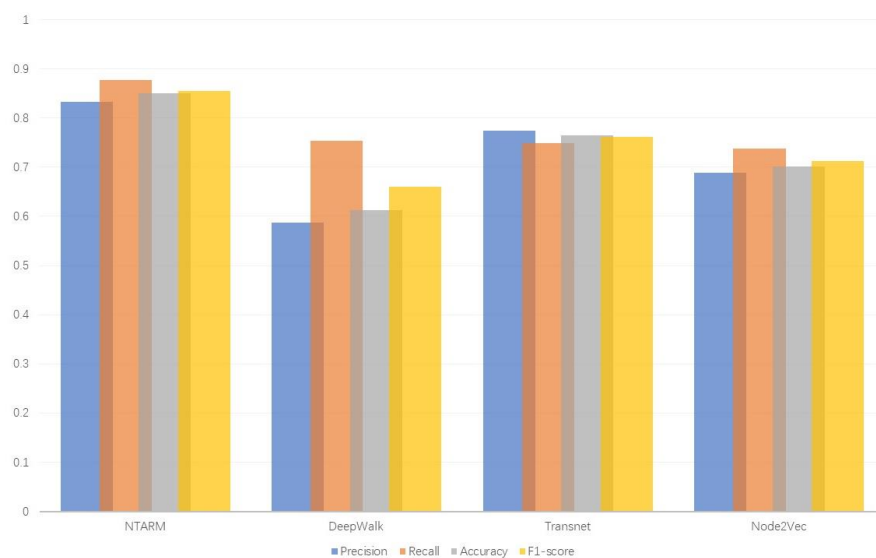
#### 5.2.2. Results and Analysis

This section describes a series of specific experiments and provides analyses to evaluate the effectiveness and applicability of the proposed mentorship relationship identification model NTARM, in comparison with several network representation learning methods and existing mentorship relationship identification models. Firstly, we compare the proposed NTARM model with the network representation learning methods mentioned in Section 5.2.1 across various research domains, including computer science, neuroscience, mathematics and chemistry. The detailed comparison results are presented in Figure 3.

This study divided the original dataset into training and testing sets in an 8:2 ratio based on the collaboration time between mentors and students. Experimental results demonstrate that the proposed NTARM model significantly enhances performance in mentor–mentee relationship identification tasks across various research domains, such as computer science. This indicates the effectiveness of the NTARM model. Specifically, among network representation learning methods, the Transnet model outperforms both DeepWalk and Node2Vec methods across all domains, underscoring the unique advantages of knowledge graph domain transfer concepts in advisor–advisee relationship identification tasks.

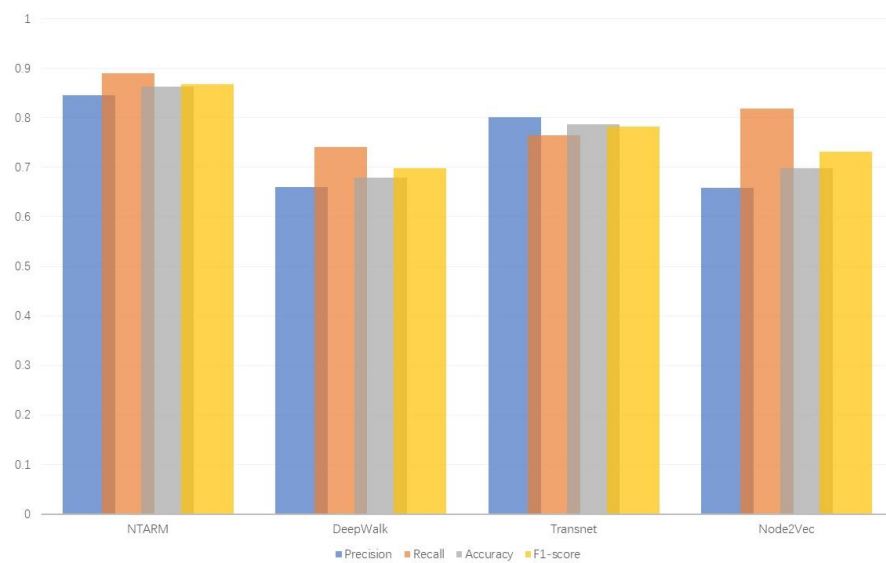


(a) Computer Science

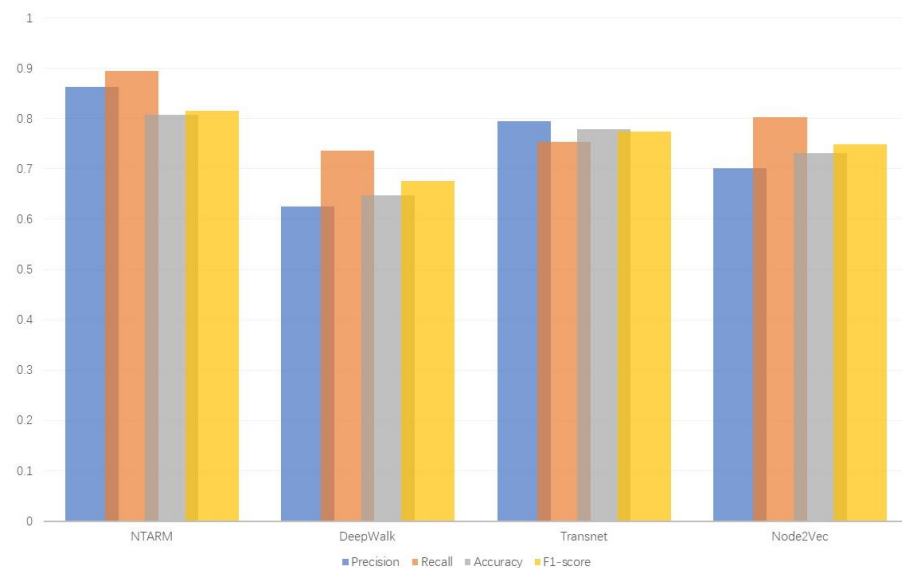


(b) Neuroscience

Figure 3. Cont.



(c) Mathematics



(d) Chemistry

**Figure 3.** Mentorship relationship identification performance comparison (compared with network representation learning methods).

Subsequently, experiments and comparisons were conducted on the NTARM model and other state-of-the-art mentor–mentee relationship identification models mentioned in Section 5.2.1, across research domains including computer science, neuroscience, mathematics and chemistry. Detailed comparison results are presented in Table 5.

Additionally, NTARM demonstrates superior performance compared to advanced mentor–mentee relationship identification models across all research domains. The incorporation of semantic information and attribute features on collaboration edges in Shifu2 results in a noticeable enhancement in its performance compared to Shifu. Furthermore, the comprehensive comparisons presented in Figure 3 and Table 5 indicate that the proposed NTARM model consistently performs well in computer science, neuroscience, mathematics and chemistry, highlighting its universality and its ability to overcome disciplinary disparities effectively.

**Table 5.** Comparison of advisor–advisee relationship identification performance.

| Computer Science |         |       |       |        | Neuroscience |       |       |        |
|------------------|---------|-------|-------|--------|--------------|-------|-------|--------|
| Metrics          | Methods | NTARM | Shifu | Shifu2 | Metrics      | NTARM | Shifu | Shifu2 |
| Precision        |         | 0.855 | 0.793 | 0.814  | Precision    | 0.833 | 0.757 | 0.786  |
| Recall           |         | 0.893 | 0.824 | 0.880  | Recall       | 0.877 | 0.797 | 0.863  |
| Accuracy         |         | 0.871 | 0.804 | 0.839  | Accuracy     | 0.851 | 0.771 | 0.823  |
| F1-score         |         | 0.874 | 0.808 | 0.845  | F1-score     | 0.855 | 0.776 | 0.814  |

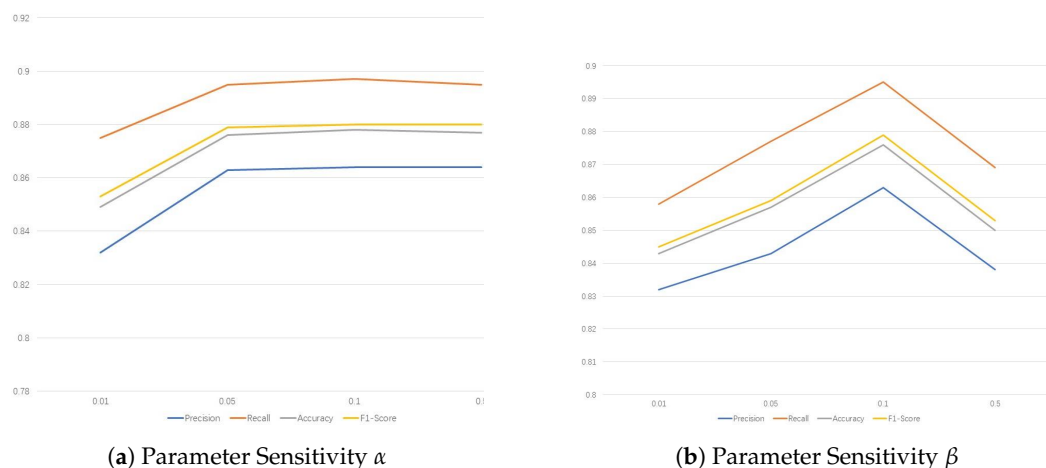
| Mathematics |         |       |       |        | Chemistry |       |       |        |
|-------------|---------|-------|-------|--------|-----------|-------|-------|--------|
| Metrics     | Methods | NTARM | Shifu | Shifu2 | Metrics   | NTARM | Shifu | Shifu2 |
| Precision   |         | 0.845 | 0.775 | 0.817  | Precision | 0.863 | 0.786 | 0.814  |
| Recall      |         | 0.890 | 0.819 | 0.882  | Recall    | 0.895 | 0.846 | 0.867  |
| Accuracy    |         | 0.863 | 0.791 | 0.842  | Accuracy  | 0.876 | 0.808 | 0.834  |
| F1-score    |         | 0.867 | 0.797 | 0.849  | F1-score  | 0.879 | 0.815 | 0.839  |

### 5.2.3. Parameter Sensitivity

This subsection delves into the sensitivity analysis of two critical hyperparameters,  $\alpha$  and  $\beta$ , on the performance of the NTARM model, elucidating their impacts and optimizing their values for enhanced model efficacy.

#### Sensitivity to $\alpha$

Hyperparameter  $\alpha$  modulates the significance of the edge deep autoencoder in the combined loss function of the model. In the realm of chemistry, an exploratory search for  $\alpha$ 's optimal value was conducted within the range [0.01, 0.05, 0.1, 0.5], keeping other hyperparameters constant. The variations in the performance of the NTARM model with different  $\alpha$  settings are illustrated in Figure 4a.

**Figure 4.** Parameter sensitivity experiment of advisor–advisee relationship recognition models.

The investigation revealed a performance increment in the NTARM model with an increase in  $\alpha$ . Notably, the model's performance begins to plateau upon reaching an  $\alpha$  value of 0.05, beyond which further increments in  $\alpha$  cease to significantly enhance performance, indicating a threshold of sensitivity to  $\alpha$ .

#### Sensitivity to $\beta$

Hyperparameter  $\beta$  influences the weight of the transition module within the joint loss function. With  $\alpha$  set to 0.05, the search for the ideal  $\beta$  spanned the range [0.01, 0.05, 0.1, 0.5]. Figure 4b captures the NTARM model's performance dynamics across varied  $\beta$  settings.

The results indicate a continuous improvement in the NTARM model's performance with increasing  $\beta$  values, reaching an apex at  $\beta = 0.1$ , after which the performance begins to wane. This pattern underscores the auxiliary role of the transition module in mentor–mentee relationship identification. Smaller  $\beta$  values prove insufficient for augmenting model performance, whereas excessively large  $\beta$  values may disrupt the task-specific learning process during gradient descent.

The parameter sensitivity analysis underscores the importance of judicious hyperparameter tuning for the optimal performance of the NTARM model, illustrating the critical balance required in weighting the model components' contributions to the overall learning objective.

### 5.3. Experiments on the Student Academic Paper Social Recommendation Model

This section evaluates the Student Social Recommendation Model for Academic Papers (SSRES) introduced in Section 4.4, to verify its recommendation performance and the significant improvement brought by constructing academic social relationships among students as discussed in Section 4 through ablation studies. As previously mentioned, the experiments utilize the Aminer and AFT datasets, which have been aligned and preprocessed for the experiments. Due to the large size of the original datasets, a subset containing a portion of the original data was used for the experiments in this section, including student nodes, paper nodes, ratings of papers by students, and social information among students, as detailed in Table 6.

**Table 6.** Statistical data of the experimental sub-dataset.

| Data Category              | Amount   |
|----------------------------|----------|
| Number of Students         | 10,929   |
| Number of Papers           | 89,013   |
| Number of Ratings          | 281,319  |
| Number of Social Relations | 90,686   |
| Rating Density             | 0.0289%  |
| Social Density             | 0.15240% |

#### 5.3.1. Evaluation Metrics and Comparison Methods

The experiments employ commonly used metrics for Top-N recommendation tasks, namely Precision@N, Recall@N, and NDCG@N, with N set to 10. NDCG is one of the most commonly used ranking evaluation metrics, measuring the quality of the ranking of the recommended list against the true items, calculated as follows:

$$NDCG = \frac{DCG}{IDCG} \quad (35)$$

$$DCG = rel_1 + \sum_{i=2}^N \frac{rel_i}{\log_2 i} \quad (36)$$

where  $DCG$  increases the impact of items ranked higher in the sequence and decreases the impact of items ranked lower. Specifically, if the  $i$ -th item in the sequence is relevant, then  $rel_i = 1$ , otherwise  $rel_i = 0$ , and  $IDCG$  is the ideal  $DCG$  in the sequence's optimal state.

To validate the effectiveness of the SSRES model, it is compared against traditional recommendation methods, such as BPR, BPRMF and NeuMF, paper-hybrid recommendation methods, like CTR and UAGMT, and graph neural network-based recommendation methods, including LightGCN, DHCF, and DiffNet++:

- BPR [54] is a method that derives the maximum posterior probability based on Bayesian analysis and optimizes the model through stochastic gradient descent for personalized ranking recommendations.
- SBPR [55] improves upon BPR by estimating users' relative preferences in the form of rankings based on BPR and social relationships.

- NeuMF [56] uses a neural network architecture to learn the interactions between user and item features for recommendations.
- CTR [57] combines the advantages of traditional matrix factorization-based collaborative filtering and probabilistic topic models to recommend existing and newly published academic papers to users.
- UAGMT [58] is an efficient and straightforward dual-relational graph model for recommending newly published academic papers by integrating valuable information, such as readers, tags, content and citations, into the graph.
- LightGCN [59] simplifies the design of graph convolutional networks (GCN) by using only neighborhood aggregation for collaborative filtering.
- DHCF [60] introduces a dual-channel hypergraph collaborative filtering framework that incorporates a dual-channel learning strategy and models users and items using a hypergraph structure.
- DiffNet++ [61] is an improved version of the DiffNet model, modeling neural influence diffusion and interest diffusion within a unified framework.

### 5.3.2. Results and Analysis

The SSRES model is compared against existing recommendation methods in a series of experiments to evaluate its recommendation performance. The experimental comparison results are presented in Table 7. From these results, the SSRES model demonstrates outstanding performance in the academic paper recommendation task across all evaluation metrics, proving its effectiveness in recommending academic papers to students.

**Table 7.** Comparison of paper recommendation performance.

| Methods<br>Metrics | Precision@10 | Recall@10 | NDCG@10 |
|--------------------|--------------|-----------|---------|
| BPR                | 0.0101       | 0.0164    | 0.0134  |
| SBPR               | 0.0365       | 0.0877    | 0.0779  |
| NeuMF              | 0.0272       | 0.0775    | 0.0676  |
| CTR                | 0.0425       | 0.1148    | 0.1021  |
| UAGMT              | 0.0565       | 0.1217    | 0.1162  |
| LightGCN           | 0.0544       | 0.1065    | 0.1056  |
| DHCF               | 0.0529       | 0.1080    | 0.1062  |
| DiffNet++          | 0.0567       | 0.1282    | 0.1181  |
| SSRES              | 0.0586       | 0.1387    | 0.1251  |

Compared to traditional recommendation methods, paper-hybrid recommendation methods, and graph neural network-based recommendation methods, traditional recommendation methods perform the most modestly. Even the least performing paper-hybrid and graph neural network-based methods outperform traditional methods, with the UAGMT model and the DiffNet++ model showing considerable competitiveness in the student academic paper recommendation task.

### 5.3.3. Parameter Sensitivity

In this section, we explore the influence of several key hyperparameters on the performance of the SSRES model, specifically  $\delta$ , the learning rate, and the embedding dimension.

#### Sensitivity to $\delta$

Hyperparameter  $\delta$  governs the weight of the self-supervised learning module for student and paper representations within the model's joint loss. We searched for the optimal value of  $\delta$  within the range [0.005, 0.01, 0.05, 0.1], and the performance of the SSRES model with various  $\delta$  values is shown in Figure 5a.

As Figure 5a illustrates, the SSRES model's performance varies with changes in  $\delta$ , peaking at a  $\delta$  value of 0.05 before starting to decline. Therefore, in our experiments, we set  $\delta$  to 0.05.

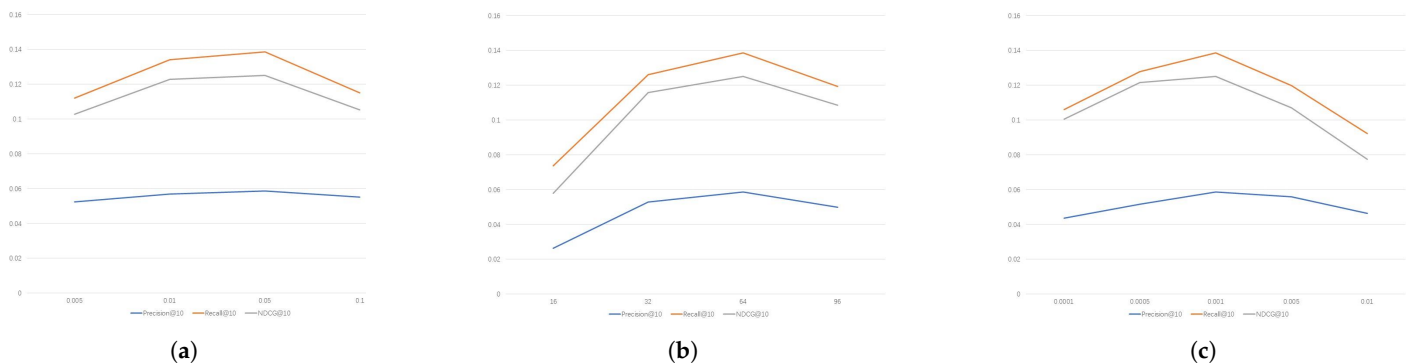


**Figure 5.** Mentorship relationship identification performance comparison (compared with network representation learning methods): (a) Parameter sensitivity to  $\delta$ ; (b) Effect of embedding dimensionality on SSRES model performance; (c) Effect of learning rate on SSRES model performance.

#### Influence of Embedding Dimension

The embedding dimension, a manually set parameter, is crucial in the learning process of comprehensive embeddings for students and academic papers. We investigated the impact of embedding dimension on the SSRES model's performance across the range [16, 32, 64, 96], with the results depicted in Figure 5b.

As shown in Figure 5b, the SSRES model's performance varies under different embedding dimensions. With Precision@10 as an example, the model's performance continually improves with increasing embedding dimension, peaking at 64 before beginning to decrease. Consequently, we set the embedding dimension to 64 for our experiments.

#### Impact of Learning Rate

The learning rate determines the update speed of the model. A too-high learning rate can cause the loss function to oscillate around the minimum value without converging, while a too-low rate makes the learning process excessively slow. We explored the impact of the learning rate on the SSRES model within the range [0.0001, 0.0005, 0.001, 0.005, 0.01], as depicted in Figure 5c.

As demonstrated in Figure 5c, the model's performance peaks at a learning rate of 0.001. Therefore, we set the learning rate to 0.001 for our experiments.

This sensitivity analysis illustrates the significant role that the hyperparameters  $\delta$ , embedding dimension, and learning rate play in optimizing the SSRES model's performance.

#### 5.4. Ablation Study

This section presents an ablation study to verify the contribution of various components within the proposed SSRES model to the final recommendation performance. Three variants of the model are introduced for this purpose: SSRES-HE, SSRES-AR, and SSRES-SP.

- SSRES-HE is a variant where the high-order social relationships “co-authorship” and “co-citation” are modeled and learned as binary relations within the SSRES framework.
- SSRES-AR modifies the sample selection strategy in the cross-relationship contrastive learning framework of SSRES, treating the student node itself as a positive sample and all other student nodes as negative samples.
- SSRES-SP is the version of the SSRES model without the paper contrastive learning architecture.

The results of the ablation study are shown in Table 8.

**Table 8.** Ablation study results.

| Model    | Precision@10 | Recall@10 | NDCG@10 |
|----------|--------------|-----------|---------|
| SSRES-HE | 0.0549       | 0.1261    | 0.1183  |
| SSRES-AR | 0.0519       | 0.1255    | 0.1136  |
| SSRES-SP | 0.0487       | 0.1194    | 0.1088  |
| SSRES    | 0.0586       | 0.1387    | 0.1251  |

From the results in Table 8, it is clear that the SSRES model outperforms the SSRES-HE and SSRES-AR variants in all aspects, which thoroughly demonstrates the significant role of the academic social relationships constructed in Section 4 in enhancing the recommendation effects of the SSRES model. Compared to SSRES-HE, which models high-order social relationships as binary relations and uses graph neural networks for learning, the performance of SSRES-AR is even less satisfactory. This highlights the importance of high-quality self-supervised signals for the self-supervised student representation learning process. Furthermore, the superior performance of SSRES over SSRES-SP underscores that capturing additional information on papers, a crucial explicit representation in academic networks, and refining and learning paper embeddings are indispensable components of the recommendation process. Relying solely on student–paper interaction data for learning paper representations is insufficient.

## 6. Discussion and Conclusions

The SSRES model represents a significant advancement in academic paper recommendation systems, effectively addressing the challenges of academic information overload and learning disorientation faced by students. The SSRES model integrates multiple information to reflect the complex relationships of academic paper recommendation systems, combining hypergraphs and networks to express high-order social relationships, a dual-structured enhancement to connect students' social information and academic papers, and self-supervised learning frameworks to complete the recommendation task.

Through the innovative integration of high-order social relationships within the academic social network, SSRES not only refines the recommendation process but also enhances the model's understanding of students' diverse academic backgrounds and preferences. This study underscores the model's effectiveness in leveraging social homophily principles, thereby providing tailored academic resources that foster personalized learning experiences.

Critically, the construction of a multifaceted academic social network emerges as a cornerstone of the SSRES model, enabling a nuanced understanding of complex student interactions and academic interests. The employment of self-supervised learning techniques further distinguishes SSRES, optimizing the representation of both students and academic papers through a contrastive learning framework that captures the essence of academic social relationships and interactions.

Empirical evaluations on real-world datasets reveal the SSRES model's superior performance, particularly in mining mentor–mentee relationships within academic networks. This validation not only attests to the model's robustness but also highlights its potential in transforming academic paper recommendation systems.

Looking forward, the exploration of more comprehensive datasets and the refinement of mentor–mentee relationship mining techniques present promising avenues for future research. Addressing the cold-start problem remains a pivotal challenge, inviting innovative approaches to enhance the SSRES model's applicability across diverse academic settings. This study's insights pave the way for the development of more effective, efficient, and personalized academic recommendation systems, marking a significant contribution to the field of educational technology.

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## References

1. Berkovsky, S.; Freyne, J. Group-based recipe recommendations: Analysis of data aggregation strategies. In Proceedings of the Fourth ACM Conference on Recommender Systems, New York, NY, USA, 26 September 2010; pp. 111–118.
2. Pujahari, A.; Padmanabhan, V. Group recommender systems: Combining user-user and item-item collaborative filtering techniques. In Proceedings of the 2015 International Conference on Information Technology (ICIT), Bhubaneswar, India, 21–23 December 2015; IEEE: Piscataway, NJ, USA, 2015; pp. 148–152.
3. Dwivedi, P.; Bharadwaj, K.K. e-Learning recommender system for a group of learners based on the unified learner profile approach. *Expert Syst.* **2015**, *32*, 264–276. [\[CrossRef\]](#)
4. Papamitsiou, Z.; Economides, A.A. Recommendation of educational resources to groups: A game-theoretic approach. In Proceedings of the 2018 IEEE Global Engineering Education Conference (EDUCON), Santa Cruz de Tenerife, Spain, 17–20 April 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 760–767.
5. Kompan, M.; Bielikova, M. Enhancing existing e-learning systems by single and group recommendations. *Int. J. Contin. Eng. Educ. Life Long Learn.* **2016**, *26*, 386–404. [\[CrossRef\]](#)
6. Zapata, A.; Menéndez, V.H.; Prieto, M.E.; Romero, C. Evaluation and selection of group recommendation strategies for collaborative searching of learning objects. *Int. J. Hum.-Comput. Stud.* **2015**, *76*, 22–39. [\[CrossRef\]](#)
7. Papamitsiou, Z.; Economides, A.A. Motivating students in collaborative activities with game-theoretic group recommendations. *IEEE Trans. Learn. Technol.* **2018**, *13*, 374–386. [\[CrossRef\]](#)
8. Beel, J.; Gipp, B.; Langer, S.; Breiting, C. Paper recommender systems: A literature survey. *Int. J. Digit. Libr.* **2016**, *17*, 305–338. [\[CrossRef\]](#)
9. Bai, X.; Wang, M.; Lee, I.; Yang, Z.; Kong, X.; Xia, F. Scientific paper recommendation: A survey. *IEEE Access* **2019**, *7*, 9324–9339. [\[CrossRef\]](#)
10. Bauer, J.; Nanopoulos, A. Recommender systems based on quantitative implicit customer feedback. *Decis. Support Syst.* **2014**, *68*, 77–88. [\[CrossRef\]](#)
11. Langseth, H.; Nielsen, T.D. Scalable learning of probabilistic latent models for collaborative filtering. *Decis. Support Syst.* **2015**, *74*, 1–11. [\[CrossRef\]](#)
12. Barragáns-Martínez, A.B.; Costa-Montenegro, E.; Burguillo, J.C.; Rey-López, M.; Mikic-Fonte, F.A.; Peleteiro, A. A hybrid content-based and item-based collaborative filtering approach to recommend TV programs enhanced with singular value decomposition. *Inf. Sci.* **2010**, *180*, 4290–4311. [\[CrossRef\]](#)
13. Park, D.H.; Kim, H.K.; Choi, I.Y.; Kim, J.K. A literature review and classification of recommender systems research. *Expert Syst. Appl.* **2012**, *39*, 10059–10072. [\[CrossRef\]](#)
14. Son, J.; Kim, S.B. Academic paper recommender system using multilevel simultaneous citation networks. *Decis. Support Syst.* **2018**, *105*, 24–33. [\[CrossRef\]](#)
15. Ferrara, F.; Pudota, N.; Tasso, C. A keyphrase-based paper recommender system. In Proceedings of the Digital Libraries and Archives: 7th Italian Research Conference, IRCDL 2011, Pisa, Italy, 20–21 January 2011; Revised Papers 7; Springer: Berlin/Heidelberg, Germany, 2011; pp. 14–25.
16. Steurer, M.; Trattner, C. Acquaintance or partner? Predicting partnership in online and location-based social networks. In Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, Niagara Falls, ON, Canada, 25–28 August 2013; pp. 372–379.
17. Liu, J.; Kong, X.; Xia, F.; Bai, X.; Wang, L.; Qing, Q.; Lee, I. Artificial intelligence in the 21st century. *IEEE Access* **2018**, *6*, 34403–34421. [\[CrossRef\]](#)
18. Xia, F.; Wang, W.; Bekele, T.M.; Liu, H. Big scholarly data: A survey. *IEEE Trans. Big Data* **2017**, *3*, 18–35. [\[CrossRef\]](#)

19. Fortunato, S.; Bergstrom, C.T.; Börner, K.; Evans, J.A.; Helbing, D.; Milojević, S.; Petersen, A.M.; Radicchi, F.; Sinatra, R.; Uzzi, B.; et al. Science of science. *Science* **2018**, *359*, eaao0185. [[CrossRef](#)] [[PubMed](#)]
20. Wang, W.; Cui, Z.; Gao, T.; Yu, S.; Kong, X.; Xia, F. Is scientific collaboration sustainability predictable? In Proceedings of the 26th International Conference on World Wide Web Companion, Perth, Australia, 3–7 April 2017; pp. 853–854.
21. Yu, S.; Xia, F.; Zhang, K.; Ning, Z.; Zhong, J.; Liu, C. Team recognition in big scholarly data: Exploring collaboration intensity. In Proceedings of the 2017 IEEE 15th Intl Conf on Dependable, Autonomic and Secure Computing, 15th Intl Conf on Pervasive Intelligence and Computing, 3rd Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech), Orlando, FL, USA, 6–10 November 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 925–932.
22. Tang, W.; Zhuang, H.; Tang, J. Learning to infer social ties in large networks. In Proceedings of the Joint European Conference on Machine Learning and Knowledge Discovery in Databases, Bilbao, Spain, 13–17 September 2011; Springer: Berlin/Heidelberg, Germany, 2011; pp. 381–397.
23. Wang, C.; Han, J.; Jia, Y.; Tang, J.; Zhang, D.; Yu, Y.; Guo, J. Mining advisor-advisee relationships from research publication networks. In Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Washington, DC, USA, 25–28 July 2010; pp. 203–212.
24. Zhao, Z.; Liu, W.; Qian, Y.; Nie, L.; Yin, Y.; Zhang, Y. Identifying advisor-advisee relationships from co-author networks via a novel deep model. *Inf. Sci.* **2018**, *466*, 258–269. [[CrossRef](#)]
25. Wang, W.; Liu, J.; Xia, F.; King, I.; Tong, H. Shifu: Deep learning based advisor-advisee relationship mining in scholarly big data. In Proceedings of the 26th International Conference on World Wide Web Companion, Perth, Australia, 3–7 April 2017; pp. 303–310.
26. Cialdini, R.B.; Goldstein, N.J. Social influence: Compliance and conformity. *Annu. Rev. Psychol.* **2004**, *55*, 591–621. [[CrossRef](#)] [[PubMed](#)]
27. McPherson, M.; Smith-Lovin, L.; Cook, J.M. Birds of a feather: Homophily in social networks. *Annu. Rev. Sociol.* **2001**, *27*, 415–444. [[CrossRef](#)]
28. Ma, H.; Yang, H.; Lyu, M.R.; King, I. Sorec: Social recommendation using probabilistic matrix factorization. In Proceedings of the 17th ACM Conference on Information and Knowledge Management, Napa Valley, CA, USA, 26–30 October 2008; pp. 931–940.
29. Ma, H.; Zhou, D.; Liu, C.; Lyu, M.R.; King, I. Recommender systems with social regularization. In Proceedings of the Fourth ACM International Conference on Web Search and Data Mining, Hong Kong, China, 9–12 February 2011; pp. 287–296.
30. Yang, B.; Lei, Y.; Liu, J.; Li, W. Social collaborative filtering by trust. *IEEE Trans. Pattern Anal. Mach. Intell.* **2016**, *39*, 1633–1647. [[CrossRef](#)]
31. Yin, H.; Wang, Q.; Zheng, K.; Li, Z.; Yang, J.; Zhou, X. Social influence-based group representation learning for group recommendation. In Proceedings of the 2019 IEEE 35th International Conference on Data Engineering (ICDE), Macao, China, 8–11 April 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 566–577.
32. Yin, H.; Wang, Q.; Zheng, K.; Li, Z.; Zhou, X. Overcoming data sparsity in group recommendation. *IEEE Trans. Knowl. Data Eng.* **2020**, *34*, 3447–3460. [[CrossRef](#)]
33. Zhou, J.; Cui, G.; Hu, S.; Zhang, Z.; Yang, C.; Liu, Z.; Wang, L.; Li, C.; Sun, M. Graph neural networks: A review of methods and applications. *AI Open* **2020**, *1*, 57–81. [[CrossRef](#)]
34. Fan, W.; Ma, Y.; Li, Q.; He, Y.; Zhao, E.; Tang, J.; Yin, D. Graph neural networks for social recommendation. In Proceedings of the The World Wide Web Conference, San Francisco, CA, USA, 13–17 May 2019; pp. 417–426.
35. Wu, Q.; Zhang, H.; Gao, X.; He, P.; Weng, P.; Gao, H.; Chen, G. Dual graph attention networks for deep latent representation of multifaceted social effects in recommender systems. In Proceedings of the The World Wide Web Conference, San Francisco, CA, USA, 13–17 May 2019; pp. 2091–2102.
36. Song, W.; Xiao, Z.; Wang, Y.; Charlin, L.; Zhang, M.; Tang, J. Session-based social recommendation via dynamic graph attention networks. In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining, Melbourne, Australia, 11–15 February 2019; pp. 555–563.
37. Wang, W.; Liu, J.; Yu, S.; Zhang, C.; Xu, Z.; Xia, F. Mining advisor-advisee relationships in scholarly big data: A deep learning approach. In Proceedings of the 16th ACM/IEEE-CS on Joint Conference on Digital Libraries, Newark, NJ, USA, 19–23 June 2016; pp. 209–210.
38. Chen, T.; Kornblith, S.; Norouzi, M.; Hinton, G. A simple framework for contrastive learning of visual representations. In Proceedings of the International Conference on Machine Learning, PMLR, Virtual Event, 13–18 July 2020; pp. 1597–1607.
39. He, K.; Fan, H.; Wu, Y.; Xie, S.; Girshick, R. Momentum contrast for unsupervised visual representation learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Seattle, WA, USA, 14–19 June 2020; pp. 9729–9738.
40. Veličković, P.; Fedus, W.; Hamilton, W.L.; Liò, P.; Bengio, Y.; Hjelm, R.D. Deep graph infomax. *arXiv* **2018**, arXiv:1809.10341.
41. Peng, Z.; Huang, W.; Luo, M.; Zheng, Q.; Rong, Y.; Xu, T.; Huang, J. Graph representation learning via graphical mutual information maximization. In Proceedings of the Web Conference 2020, Taipei, Taiwan, 20–24 April 2020; pp. 259–270.
42. Hassani, K.; Khasahmadi, A.H. Contrastive multi-view representation learning on graphs. In Proceedings of the International Conference on Machine Learning, PMLR, Virtual, 13–18 July 2020; pp. 4116–4126.
43. Park, C.; Kim, D.; Han, J.; Yu, H. Unsupervised attributed multiplex network embedding. *Aaai Conf. Artif. Intell.* **2020**, *34*, 5371–5378. [[CrossRef](#)]

44. Dunbar, R. *How Many Friends Does One Person Need? Dunbar's Number and Other Evolutionary Quirks*; Harvard University Press: Cambridge, MA, USA, 2010.
45. Qin, D.; Zhou, X.; Chen, L.; Huang, G.; Zhang, Y. Dynamic connection-based social group recommendation. *IEEE Trans. Knowl. Data Eng.* **2018**, *32*, 453–467. [[CrossRef](#)]
46. Tang, J.; Zhang, J.; Yao, L.; Li, J.; Zhang, L.; Su, Z. Arnetminer: Extraction and mining of academic social networks. In Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Las Vegas, NV, USA, 24–27 August 2008; pp. 990–998.
47. Liénard, J.F.; Achakulvisut, T.; Acuna, D.E.; David, S.V. Intellectual synthesis in mentorship determines success in academic careers. *Nat. Commun.* **2018**, *9*, 4840. [[CrossRef](#)] [[PubMed](#)]
48. Iglič, H.; Doreian, P.; Kronegger, L.; Ferligoj, A. With whom do researchers collaborate and why? *Scientometrics* **2017**, *112*, 153–174. [[CrossRef](#)] [[PubMed](#)]
49. Montoya, F.G.; Alcayde, A.; Baños, R.; Manzano-Agugliaro, F. A fast method for identifying worldwide scientific collaborations using the Scopus database. *Telemat. Inform.* **2018**, *35*, 168–185. [[CrossRef](#)]
50. Perozzi, B.; Al-Rfou, R.; Skiena, S. Deepwalk: Online learning of social representations. In Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, New York, NY, USA, 24–27 August 2014; pp. 701–710.
51. Grover, A.; Leskovec, J. node2vec: Scalable feature learning for networks. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 13–17 August 2016; pp. 855–864.
52. Tu, C.; Zhang, Z.; Liu, Z.; Sun, M. TransNet: Translation-Based Network Representation Learning for Social Relation Extraction. In Proceedings of the IJCAI, Melbourne, Australia, 19–25 August 2017; pp. 2864–2870.
53. Liu, J.; Xia, F.; Wang, L.; Xu, B.; Kong, X.; Tong, H.; King, I. Shifu2: A network representation learning based model for advisor-advisee relationship mining. *IEEE Trans. Knowl. Data Eng.* **2019**, *33*, 1763–1777. [[CrossRef](#)]
54. Rendle, S.; Freudenthaler, C.; Gantner, Z.; Schmidt-Thieme, L. BPR: Bayesian personalized ranking from implicit feedback. *arXiv* **2012**, arXiv:1205.2618.
55. Zhao, T.; McAuley, J.; King, I. Leveraging social connections to improve personalized ranking for collaborative filtering. In Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management, Shanghai China, 3–7 November 2014; pp. 261–270.
56. He, X.; Liao, L.; Zhang, H.; Nie, L.; Hu, X.; Chua, T.S. Neural collaborative filtering. In Proceedings of the 26th International Conference on World Wide Web, Perth, Australia, 3–7 April 2017; pp. 173–182.
57. Wang, C.; Blei, D.M. Collaborative topic modeling for recommending scientific articles. In Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Diego, CA, USA, 21–24 August 2011; pp. 448–456.
58. Cai, T.; Cheng, H.; Luo, J.; Zhou, S. An efficient and simple graph model for scientific article cold start recommendation. In Proceedings of the Conceptual Modeling: 35th International Conference, ER 2016, Gifu, Japan, 14–17 November 2016, Proceedings 35; Springer: Berlin/Heidelberg, Germany, 2016; pp. 248–259.
59. He, X.; Deng, K.; Wang, X.; Li, Y.; Zhang, Y.; Wang, M. Lightgcn: Simplifying and powering graph convolution network for recommendation. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval, Xi'an, China, 25–30 July 2020; pp. 639–648.
60. Ji, S.; Feng, Y.; Ji, R.; Zhao, X.; Tang, W.; Gao, Y. Dual channel hypergraph collaborative filtering. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, Virtual Event, CA, USA, 6–10 July 2020; pp. 2020–2029.
61. Wu, L.; Li, J.; Sun, P.; Hong, R.; Ge, Y.; Wang, M. Diffnet++: A neural influence and interest diffusion network for social recommendation. *IEEE Trans. Knowl. Data Eng.* **2020**, *34*, 4753–4766. [[CrossRef](#)]

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